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Assessing the abatement potential and cost of Chinese industrial water pollutants

Huiming Xie[a,b], Manhong Shen[b,c] and Chu Wei[d]

[a]School of Economics and Management, Zhejiang Sci-tech University, Hangzhou 310018, China
[b]Center for Ecological Civilization of Zhejiang Province, Zhejiang Sci-tech University, Hangzhou 310018, China
[c]School of Business, Ningbo University, Ningbo 315211, China
[d]Corresponding author. School of Economics, Renmin University, Beijing 100872, China. E-mail: xiaochu1979@gmail.com

Abstract

Water pollution is becoming an increasing threat to China's sustainable development. To respond to this challenge, China has pledged to cut emissions of two major water pollutants, chemical oxygen demand (COD) and ammonia nitrogen (NH_4), and has disaggregated the national target among provinces. However, the abatement potential and costs have not been thoroughly assessed. This paper aims to examine the reduction potential and associated costs of COD and NH_4 in the Chinese industrial sector. A parametric directional distance function is applied to modeling joint production, in which COD and NH_4 are treated simultaneously as byproducts of the production process. Using provincial data from 2003 to 2012, we find that 13.18% of COD and 13.27% of NH_4 can be reduced if all provinces perform efficiently. The average abatement cost to cut one additional unit of COD and NH_4 is 710 and 7,390 Yuan/kg, respectively. The abatement cost is significantly correlated with the economic development level, pollution intensity and capital-labor ratio. Our results call for a market-based instrument, such as an Emission Trading System, to assist China in achieving this environmental goal in a cost-effective way. Moreover, it will become more difficult and costly to control COD, while there still exists a 'win-win' opportunity to control NH_4 emissions through efficiency improvements.

Keywords: Abatement cost; Abatement potential; Chinese industrial sector; Water pollutant

1. Introduction

China is suffering escalating negative consequences from environmental pollution, e.g., increasing respiratory diseases and mortality (Zhang *et al.*, 2010) and water-related food safety risk (Jawahar & Ringler, 2009). Water pollution is less visible but has emerged as more threatening over time (World Bank 2007; Wu *et al.*, 2015). Water pollution has a direct and negative impact on public health (more sick days, more cancer, etc.), the ecological system (more pollution in developed areas) and

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economic development (tourism, fisheries, hunting, etc.) (Stonich, 1998; Hu & Cheng, 2013; Wang & Yang, 2016). Taking the health impact for example, Wang & Yang (2016) reveal that water pollution in China has imposed significantly negative influence on health outcomes. Moreover, they suggest that the common pollutants in industrial wastewater have differential impacts on health outcomes. Dwight *et al.* (2005) investigate the health cost of four kinds of diseases due to exposure to polluted coastal water. They find that the average economic burden for the residents of Orange County in California will increase by about $44.63 per person. Besides, stated preference analysis (e.g. hedonic method) is also widely adopted to estimate the environmental externalities of urban river pollution or the impacts of pollution (Guignet, 2012; Chen, 2017).

In 2012, the total discharge of wastewater in China reached 68.5×10^9 tons which is, in volume terms, comparable to the annual flow of the Yellow River of 58×10^9 m^3 per annum (National Bureau of Statistics, 2014). According to the Ministry of Environmental Protection (MEP) of China, 61.5% of groundwater monitoring sites do not meet the average water quality standard. Among the 968 sections of 423 major rivers and lakes under national monitoring, 63.1% of sections had water quality ratings from Grade I to III, 27.7% from Grade IV to V, and 9.2% Grade V and below[1] (MEP, 2014, 2008). The most important and most thoroughly collected indicators of wastewater in China are the chemical oxygen demand (COD) and ammonia nitrogen (NH_4), which are also the two main objects of government regulation.

To cope with the challenge, the Chinese government has issued and implemented many water policies in the past several decades. The strictest and most effective way to achieve a mitigation target for water pollutants is implementation of a total emission control policy for wastewater. The policy was first introduced in 1988 with the efforts of the Environmental Protection Bureau of China (the former body of MEP) to implement the '*Interim Measures for the Administration of Water Pollution Discharge Permits*'. Until 1996, when the State Council of China promulgated the '*Decision on Several Issues Concerning Environmental Protection*', the quantity of wastewater was targeted at a certain level and each region was required to meet a basic concentration standard for wastewater. The policy has recently been shifted to control the quantity of specific water pollutants according to the environmental carrying capacity of water.

During the 10th Five-Year-Plan (FYP, 2001–2005), China planned to mitigate specific pollutants and set a non-binding target of a 10% reduction of national SO_2 and COD emissions. However, emissions of SO_2 and soot increased by 8–15% in 2003 and most indexes of environmental protection failed to meet the target. During the 11th FYP (2006–2010), the central government committed to a mandatory target to cut 10% of national SO_2 and COD emissions. This binding goal was also distributed among provinces. At the end of the 11th FYP, the country as a whole accomplished a 12.45% reduction of COD and a 14.29% reduction of SO_2. In the 12th FYP (2011–2015), China has continued a policy of reducing the main pollutants and added two more pollutants, NH_4 and NOx, to the policy. The corresponding national abatement targets for NH_4 and NOx are set at 10%, while for SO_2 and COD the targets are 8% nationwide.

Although the government has made great efforts in response to these urgent practical needs, the subject has attracted less attention from the academic community. Environmental scientists usually focus on the driving forces of water pollutants. Nevertheless, assessment studies of water pollutant reduction

[1] In China, the worst grade of water quality is defined as Grade V and below while Grade I is the best.

potential and costs are rare. Most assessment studies have assessed the potential to reduce the use of energy or reduce emissions of air pollutants (Price *et al*., 2011; Wei *et al*., 2015). Some studies estimate the potential water savings for the agricultural sector (Ensink *et al.*, 2004; Hongyun & Liange, 2007; Christian-Smith *et al*., 2012; Bassi, 2014). Recently, Ng (2015) estimated the cost of seawater flushing for 15 major coastal cities. However, to the best of our knowledge, few studies have investigated the feasible reduction potential and marginal cost to cut industrial water pollution in China. This paper aims to fill this gap.

Our paper focuses on industrial COD and NH_4 emissions, which are controlled by the 11th FYP and the 12th FYP, respectively. Using data covering the 10th, 11th and 12th FYP (2003–2012), we investigate dynamic change and spatial variation in terms of abatement potential and abatement cost, which conveys important policy implications. We employ environmental production theory and a directional distance function (DDF) to model the multi-input and multi-output structure and the simultaneous production of pollutants. This approach has a flexible structure that enables researchers to derive interesting results, such as the marginal cost of abating various pollutants (Färe *et al*., 2005, 2006). Our results show that 13.18% of national COD and 13.27% of national NH_4 are over-emitted due to inefficiency[2]. For the period 2003–2012, the average cost to abate one additional unit of COD was 710 Yuan/kg and the average cost to abate an additional unit of NH_4 was 7,390 Yuan/kg. We further investigate the determinants of the abatement cost using a fixed-effect panel estimation. Our estimation indicates that the abatement cost is a function of the economic development level, pollution intensity and capital-labor ratio. We find that pollution abatement policies affect abatement costs through various channels. Moreover, our results suggest that the abatement of COD is becoming more costly and difficult, while reduction of NH_4 presents 'win-win' opportunities.

The paper is presented as follows. Section 2 introduces the model and presents the empirical specification. Section 3 presents the data and variables. Section 4 reports the main results and Section 5 presents a further discussion. The conclusion and policy implications are presented in Section 6.

2. Model and specification

Environmental efficiency, surely including the water environment, urgently needs to be studied and the method incorporating both the desirable and undesirable outputs needs be further extended (Song *et al*., 2012, 2013). We use a framework of environmental production technology and the DDF to model the efficiency assessment. This enables us to further investigate the abatement potential and abatement cost for industrial COD and NH_4 emissions. An environmental production technology refers to a production process such that producers employ the vector of inputs $x \in R_+^N$ to produce the desirable output vector $y \in R_+^{M_1}$ and the undesirable output vector $b \in R_+^{M_2}$, where R_+ refers to the positive real number set, and N, M_1 and M_2 refer to the limited elements for each set. In the joint-production process, the input vector often includes labor, capital, energy and resources, and the undesirable output

[2] Here the inefficiency or efficiency refers to the input-output relationship during the production process. Given the same inputs, the decision-making unit which produces more outputs than its counterpart can be treated as the more efficient one. Alternatively, the unit which utilizes the least input to produce the same output is defined as efficient.

vector includes a variety of pollutants, e.g., COD and NH_4. The technology can be expressed as

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

In the process, the inputs and desirable outputs are generally assumed to be freely disposable while the desirable and undesirable outputs are together weakly disposable. Furthermore, no desirable output can be simultaneously produced without undesirable output, which is referred to as the null-jointness assumption. The directional output distance function can be formulated as follows (Chung *et al.*, 1997):

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

where $g = (g_y, -g_b) \in R_+^{M_1} \times R_+^{M_2}$ is the directional vector, and β is the value of the DDF that measures the simultaneous maximum expansion of desirable outputs and contraction of undesirable outputs. A larger value of β means less efficiency. It can be used to represent the inefficiency level, or proxy the abatement potential (Wei *et al.*, 2012). Meanwhile, this DDF inherits all the properties of the set $P(x)$, including non-negativity, monotonicity, weak disposability and translation properties.

We adopt the parametric quadratic specification to represent the DDF because of its advantages, including differentiability, flexibility and other over-performing properties (Färe *et al.*, 2010). In our case, we have four inputs (labor, capital stock, coal and petrol), one desirable output (industrial value-added) and two undesirable outputs (COD and NH_4). Following Färe & Grosskopf (2010), the directional vector is set as $(g_y, g_b) = (1, -1)$. As for the empirical specification, there are various choices of function form to represent the DDF. For example, the widely used trans-log function. However, as Färe *et al.* (2010) suggested, the quadratic representation over-performs compared to the trans-log parameterizations. Here we use the quadratic DDF for province k in year t. It is given as

$$\begin{aligned} D(x_k^t, y_k^t, b_k^t; 1, -1) = {} & \alpha + \sum_{n=1}^{4} \alpha_n x_{n,k}^t + \beta_1 y_k^t + \sum_{n=1}^{2} \gamma_n b_{n,k}^t + \frac{1}{2}\sum_{n=1}^{4}\sum_{n'=1}^{4} \alpha_{nn'} x_{n,k}^t x_{n',k}^t + \frac{1}{2}\beta_2 (y_k^t)^2 \\ & + \frac{1}{2}\sum_{n=1}^{2}\sum_{n'=1}^{2} \gamma_{nn'} b_{n,k}^t b_{n',k}^t + \sum_{n=1}^{4}\sum_{n'=1}^{2} \eta_{nn'} x_{n,k}^t b_{n',k}^t + \sum_{n=1}^{4} \delta_n x_{n,k}^t y_{n,k}^t + \sum_{n=1}^{2} \mu_n y_{n,k}^t b_{n,k}^t \end{aligned} \tag{3}$$

Based on Equation (3), the individual heterogeneity and dynamic change are also controlled through a set of provincial and year dummies in the intercept term:

$$\alpha = \alpha_0 + \sum_{k=1}^{K-1} \lambda_k S_k + \sum_{t=1}^{T-1} \tau_t T_t \tag{4}$$

where λ_k and τ_t are the coefficients of the provincial and year dummies. The province dummy variable $S_{k'} = 1$ if $k' = k$; otherwise, it will be set to 0. There is a similar setting for the year dummy.

Following Aigner & Chu (1968), a linear programing algorithm is adopted to estimate the parameters in Equations (3) and (4). Formula (5) aims at minimizing the sum of the deviations of the distances subject to the properties of feasibility, non-jointness, monotonicity, translation and symmetry.

$$\min \sum_t \sum_k D\left(x_k^t, y_k^t, b_k^t; 1, -1\right)$$
$$s.t.$$
$$(i)\, D\left(x_k^t, y_k^t, b_k^t; 1, -1\right) \geq 0$$
$$(ii)\, D\left(x_k^t, y_k^t, 0; 1, -1\right) \leq 0$$
$$(iii)\, \frac{\partial D}{\partial b} \geq 0,\ \frac{\partial D}{\partial y} \leq 0,\ \frac{\partial D}{\partial \bar{x}} \geq 0$$
$$(iv)\, \beta_1 - \gamma_1 - \gamma_2 + 1 = 0 \qquad (5)$$
$$\beta_2 = \sum_{n=1}^{2} \sum_{n'=1}^{2} \gamma_{n,n'} = \mu_1 + \mu_2$$
$$\delta_n = \sum_{n'=1}^{2} \eta_{n,n'}$$
$$(v)\, \alpha_{n,n'} = \alpha_{n',n}$$
$$\gamma_{n,n'} = \gamma_{n',n}$$

Once all the coefficients are estimated, the shadow price of various pollutants can be expressed as follows (Färe *et al.*, 1993).

$$q = -p\left[\frac{\partial D(x, y, b; 1, -1)/\partial b}{\partial D(x, y, b; 1, -1)/\partial y}\right] \qquad (6)$$

where p and q are the price of desirable and undesirable outputs. In other words, the shadow price of undesirable outputs, such as COD and NH_4, can be expressed as the marginal rate of transformation and as the shadow price of the desirable output. Because the shadow price measures the opportunity cost to cut the undesirable output at the margin, it can be used to represent the marginal cost of pollutant control (Du *et al.*, 2015).

Moreover, we can derive the Morishima elasticity of substitution, which measures how the shadow price responds to the changes in pollution intensity (Färe *et al.*, 2005; Xie *et al.*, 2016). It is given as

$$M_{b,y} = \frac{\partial \ln(q/p)}{\partial \ln(y/b)} \qquad (7)$$

3. Data and descriptive statistics

Two major industrial water pollutants (COD and NH_4) are considered as byproducts associated with an industrial production process. The inputs (labor, capital stock, coal and petrol) and desirable output data can be collected from the official statistical yearbooks. The National Bureau of Statistics (NBS) has published industrial water pollutant data since the beginning of the 10th Five-Year-Planning (FYP) period; data for COD is available starting in 2001 and data for NH_4 starting in 2003. Our data covers 30 mainland provinces and 10 years (2003–2012). All the data is collected from the *China Statistical Year Book* (NBS, various years), *China Energy Statistical Year Book* (NBS, various years), *China Water Resources Bulletin* (MEP, various years) and *China Environment Yearbook* (NBS, various years).

In our case, the desirable output (y) is represented by the industrial value added; the capital input (x_1) is measured by the net value of fixed assets; the proxy of labor (x_2) is the annual average number of employees; and the energy input (x_3) is tons of total coal and petroleum products. The two bad outputs are tons of emissions of COD and NH_4 in the industrial wastewater. The monetary value is deflated to the 1998 constant price level. Tibet is excluded due to unavailability of data. The descriptive statistics are summarized in Table 1.

4. Results and discussion

4.1. Abatement potential of industrial COD and NH_4

In order to avoid the convergence problem when solving Equations (3) and (5), we normalize the input and output vectors by their mean values (Färe *et al.*, 2005). This indicates that the decision-making unit uses the mean input to produce the average output. Table 2 reports the estimated parameters of Equation (5), which are obtained by solving the linear programing using the General Algebraic Modeling System. There are in total 300 observations between 2003 and 2012 for 30 mainland provinces. However, the environmental production technology and the DDF must fulfill the requirement of null-jointness. It implies that the observation (y,0) is not in $P(x)$ if $D(x, y, 0) < 0$. As a result, 10 out of 300 observations violate this condition and are dropped. Moreover, eight observations are further dropped because of a zero denominator when estimating the shadow price. Finally, 282 observations are kept for further analysis.

Reading from Table 3, we can find that the mean value of the DDF is 0.106 during the whole period. This indicates that the industrial value-added could be expanded by $0.106*365.8 = 38.77 \times 10^9$ Yuan,

Table 1. Descriptive statistics of inputs and outputs.

Variable		Unit	Mean	Std. Dev.	Min	Max
Desirable output	Industrial value added (y)	10^8 CNY	3,658	4,182	88.88	24,294
Undesirable output	Industrial COD emission (b_1)	10^4 Ton	15.51	12.21	0.29	69.35
	Industrial NH_4 emission (b_2)	10^4 Ton	1.17	1.03	0.003	5.69
Inputs	Capital (x_1)	10^8 CNY	3,975	3,504	191	17,866
	Labor (x_2)	10^4 Person	266	295	9.62	1,568
	Total coal (x_3)	10^4 Ton	2,905	2,188	72	11,526
	Total petrol (x_4)	10^4 Ton	400	453	22	2,401

Table 2. Parameter estimates of DDF.

Parameters	Variables	Estimates	Parameters	Variables	Estimates
α_0	Constant item	−0.194	α_{42}	$x_4\ x_2$	0.143
α_1	x_1	0.252	α_{43}	$x_4\ x_3$	0.077
α_2	x_2	1.024	α_{44}	$x_4\ x_4$	−0.033
α_3	x_3	−0.067	β_2	y^2	−0.008
α_4	x_4	0.055	γ_{11}	b_1^2	−0.039
β_1	Y	−0.866	γ_{12}	$b_1\ b_2$	0.028
γ_1	b_1	0.130	γ_{22}	b_2^2	−0.025
γ_2	b_2	0.004	η_{11}	x_1b_1	0.169
α_{11}	$x_1\ x_1$	−0.170	η_{21}	x_2b_1	0.034
α_{12}	$x_1\ x_2$	0.138	η_{31}	x_3b_1	−0.081
α_{13}	$x_1\ x_3$	−0.125	η_{41}	x_4b_1	−0.067
α_{14}	$x_1\ x_4$	−0.173	η_{12}	x_1b_2	−0.009
α_{21}	$x_2\ x_1$	0.138	η_{22}	x_2b_2	−0.009
α_{22}	$x_2\ x_2$	−0.573	η_{32}	x_3b_2	−0.009
α_{23}	$x_2\ x_3$	0.080	η_{42}	x_4b_2	0.115
α_{24}	$x_2\ x_4$	0.143	δ_1	x_1y	0.159
α_{31}	$x_3\ x_1$	−0.125	δ_2	x_2y	0.025
α_{32}	$x_3\ x_2$	0.080	δ_3	x_3y	−0.090
α_{33}	$x_3\ x_3$	0.302	δ_4	x_4y	0.049
α_{34}	$x_3\ x_4$	0.077	μ_1	yb_1	−0.011
α_{41}	$x_4\ x_1$	−0.173	μ_2	yb_2	0.003

while COD and NH_4 emissions could be reduced by $0.106*155.1 = 16.44$ thousand tons and $0.106*11.7 = 1.24$ thousand tons, respectively, for a hypothetical province. The score of β starts increasing from 0.092 in 2003 to 0.139 in 2006, then decreases significantly until 2009; thereafter, it shows a clear upward trend. Because β measures the distance and serves as an inefficiency measurement, we can conclude that the emission performance of industrial COD and NH_4 got worse during 2003–2005, but the turning point appeared in 2006, when the 11th FYP set up the mandatory emission reduction targets. Emission performance improved for the period 2006–2009 but began turning worse in 2010[3].

The value of β reflects the difference between the present performance of a province compared with the most efficient frontier. It can be used to derive the feasible abatement quantity for specific inputs and outputs, i.e., the abatement quantity of COD = g_{b1}*β*_actual COD emission_, and the abatement quantity of NH_4 = g_{b2}*β*_actual NH_4 emission._ Accordingly, the national abatement potential can be expressed as the aggregated provincial abatement quantity over aggregated emissions. Figure 1 presents the historical trend of national abatement potential of COD and NH_4. On average, China's industrial sector can cut 13.18% of COD and 13.27% of NH_4 emissions. This can be achieved through efficiency improvements and does not need any additional input or sacrifice of industrial output. Moreover, we notice that the national abatement potential exhibits a trend similar to β; the inefficient emissions

[3] One possible explanation is the 2008 global economic crisis. To cope with the economic recession, China implemented the 'four-trillion investment program' to stimulate growth. This gave the pollution-intensive heavy industry sector a chance to survive, or even expand.

Table 3. Abatement potential, shadow price and Morishima elasticity of industrial COD and NH_4.

	2003–2012	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Abatement potential											
Mean of β (Std. Dev)											
	0.106	0.092	0.096	0.139	0.119	0.105	0.067	0.066	0.099	0.133	0.150
	(0.126)	(0.099)	(0.111)	(0.177)	(0.153)	(0.134)	(0.075)	(0.072)	(0.085)	(0.143)	(0.162)
COD: Average abatement quantity (tons)											
	21,240	20,982	23,480	37,531	29,807	21,458	11,915	11,875	18,003	17,278	20,448
COD: National abatement potential (%)											
	13.18	11.6	13.3	20.8	16.5	12.9	7.8	8.1	11.9	13.4	16.3
NH4: Average abatement quantity (tons)											
	1,661	1,699	2,041	3,571	2,474	1,542	738	702	1,009	1,330	1,536
NH4: National abatement potential (%)											
	13.27	12	14	22	17.5	13.6	7.5	7.7	10.4	12.9	15.7
Shadow price (unit: 10^8Yuan/ton)											
COD: Mean of q_1 (Std. Dev)											
	0.0071	0.0041	0.0045	0.0044	0.0074	0.0049	0.0064	0.0084	0.0083	0.0099	0.0131
	(0.0110)	(0.0017)	(0.0021)	(0.0024)	(0.0167)	(0.0041)	(0.0070)	(0.0119)	(0.0101)	(0.0138)	(0.0206)
NH_4: Mean of q_2 (Std. Dev)											
	0.0739	0.0334	0.0410	0.0501	0.1210	0.0469	0.0873	0.1152	0.0595	0.0922	0.0884
	(0.2203)	(0.0541)	(0.0637)	(0.0901)	(0.4446)	(0.0590)	(0.2378)	(0.3621)	(0.0812)	(0.1811)	(0.1675)
Morishima elasticity											
COD: Mean of M_{b_1y} (Std. Dev)											
	– 0.0899	−0.0448	−0.0511	−0.0665	−0.0854	−0.0901	−0.0949	−0.1004	−0.0978	−0.1365	−0.1378
	(0.0845)	(0.0398)	(0.0421)	(0.0650)	(0.0921)	(0.0779)	(0.0888)	(0.1098)	(0.0538)	(0.1003)	(0.0983)
NH_4: Mean of M_{b_2y} (Std. Dev)											
	0.0843	0.0998	0.0314	0.0697	0.0548	0.0460	0.0751	0.1547	0.1269	0.1180	0.0661
	(0.2473)	(0.2200)	(0.0337)	(0.1458)	(0.1392)	(0.0631)	(0.1926)	(0.5642)	(0.2564)	(0.2656)	(0.1219)

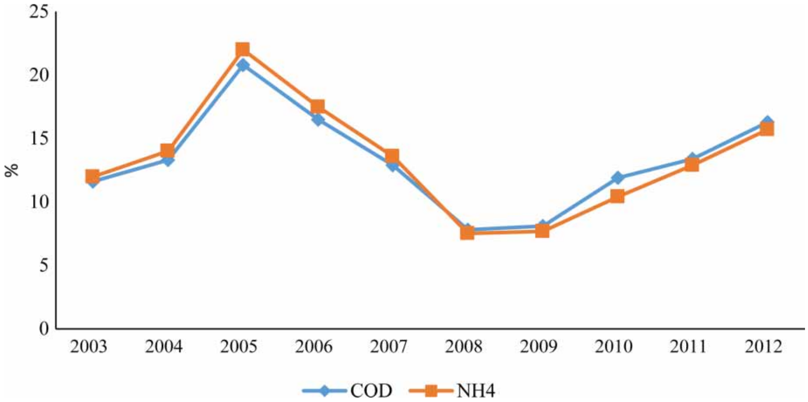

Fig. 1. The abatement potential of COD and NH_4 (2003–2012).

continuously increase and reach a peak in 2005, then turn downward to hit a valley around 2009, and thereafter increase.

We also witness a great regional disparity in Figure 2. Some provinces, like Shanxi, Beijing, Shanghai, etc., gain a low value of β during 2003–2012. This indicates these provinces are comparatively efficient. In contrast, Sichuan, Zhejiang, Shandong, Liaoning and Xinjiang are found to have a greater inefficiency score. It indicates these provinces perform worse in terms of industrial COD and NH_4 emissions.

4.2. Abatement cost of industrial COD and NH_4

As most studies have mentioned, the shadow price can serve as the marginal abatement cost because it measures the cost to reduce one additional unit of pollution (Marklund & Samakovlis, 2007; Wei *et al.*, 2012). Figure 3 depicts the relative trend of the shadow prices of COD and NH_4, taking the year 2003 as a reference (Table 3 gives details). We notice that the average marginal abatement cost to cut one ton of China's industrial COD during 2003–2012 is 0.71 million Yuan. The marginal cost

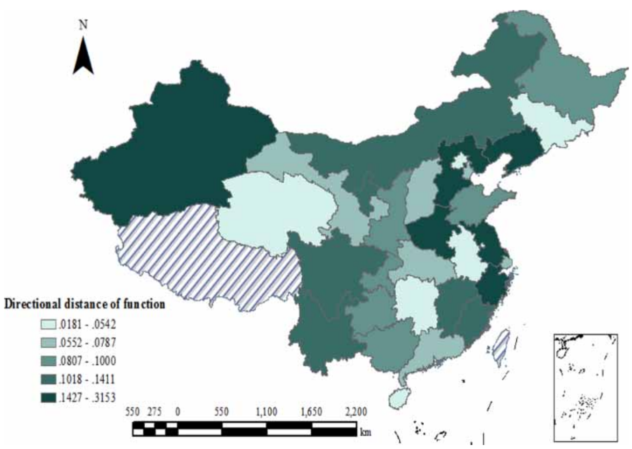

Fig. 2. Geographic distribution of average inefficiency score (2003–2012).

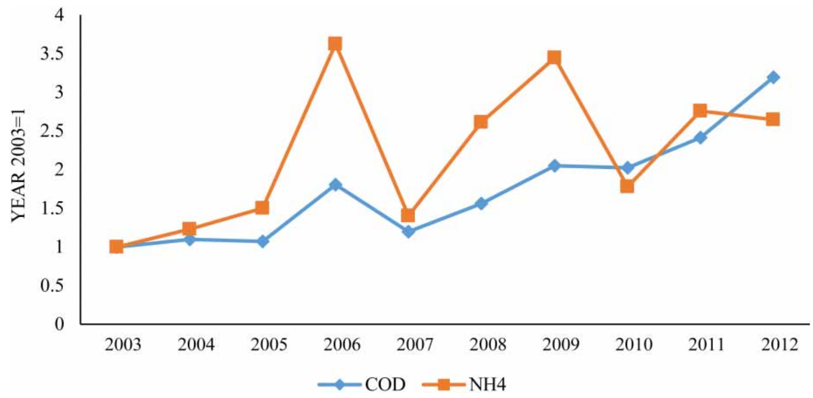

Fig. 3. The abatement cost of COD and NH_4 (2003–2012).

of NH_4 is much more expensive, about 7.39 million Yuan/ton. However, the trend varies greatly. Prior to 2006, the average abatement costs of COD and NH_4 remain broadly stable, and then jump to hit a peak in 2006. Thereafter, the industrial COD and NH_4 show different patterns. The COD abatement cost shows an upward trend. As for NH_4, its abatement cost increases during 2007–2009 and then declines, with a significant drop in 2010. In general, it is becoming more expensive to control industrial COD emissions. The overall trend of the abatement cost for NH_4 emissions is upward and fluctuating.

Figure 4 also reveals substantial regional differences in terms of pollution abatement cost. During the whole period, Guangxi, Xinjiang, Jilin and Guizhou are the provinces with the lowest abatement costs to cut industrial COD emissions, while Guangdong, Zhejiang and Jiangsu are associated with the highest abatement costs. For NH_4 reduction, Gansu, Ningxia, Guizhou, Chongqing, Anhui, Shanxi and Hunan are the provinces with the lowest abatement costs, while Guangdong, Jiangsu and Liaoning have the highest costs to control NH_4 emission. This result seems to suggest that the abatement cost in developing areas is lower, while it is much higher for developed regions. This is consistent with our intuition and previous literature (Wei *et al.*, 2012).

As shown in Table 4, we compare our results with related studies. The results vary greatly and depend on the sample data, pollutant, model and estimation strategy. For example, Wang & Lall (2002) set up a cost function in trans-log form and estimate the marginal abatement cost of water pollution based on plant-level data from 1,500 Chinese industrial firms in 1994. They find that the marginal abatement cost of COD discharge for large plants is about 582.3 Yuan per ton, and that it is much more expensive for medium-sized and small firms to reduce COD; their costs are 775.6 Yuan per ton and 1,652.3 Yuan per ton, respectively. Similarly, Dasgupta *et al.* (2001) also employ a trans-log specification to accommodate the cost function for 260 Chinese plants. Their econometric estimation suggests that the charge for COD emissions should be set at 20 \$/ton when the abatement rate is 93%. Differing from the econometric approach, Wang *et al.* (2015) use the nonparametric Data Envelopment Analysis (DEA) method to evaluate the shadow price of COD and NH_4-N for China's industrial sectors. They find that the average abatement costs for COD in 2009 and 2010 reach 69.26 Yuan/kg and 65.14 Yuan/kg, respectively. Compared to COD, the shadow price for NH_4-N is much higher. It reaches 1,646.22 Yuan/kg in 2009 and 1,446.43 Yuan/kg in 2010.

Beyond these attempts, two studies are close to our methods. Kumar & Managi (2011) use a parametric DDF to model the shadow price. Using data for 92 Indian water-polluting firms, they find the cost to cut one additional ton of COD emission ranged from 20,000 to 170,000 Rupees. Another similar study is by Tang *et al.* (2016). They also employ the parametric DDF to examine the marginal

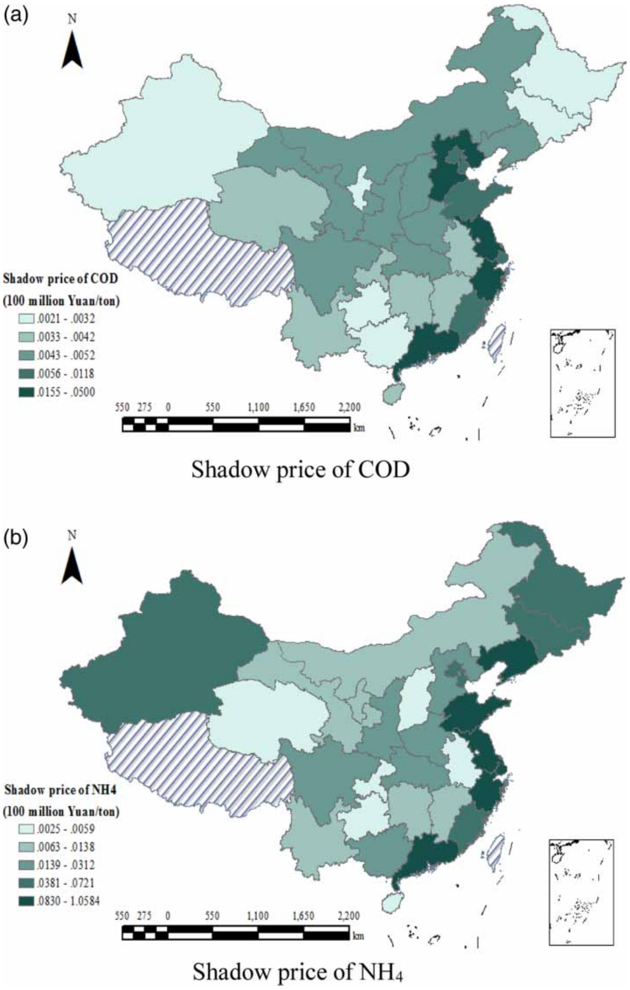

Fig. 4. Geographic distribution of abatement cost of COD and NH_4 (2003–2012).

abatement cost of COD, total nitrogen (TN) and total phosphorus (TP) emissions for the Chinese agricultural sector. Their results indicate the average shadow prices of COD, TN and TP from 2001 to 2010 are 8,266 Yuan/ton, 25,560 Yuan/ton and 10,160 Yuan/ton, respectively. In the present study, we adopt a method similar to that of Tang *et al*. (2016) but focus on the industrial sector, which has higher productivity and greater opportunity cost compared with the agricultural sector.

4.3. Elasticity of substitution

Besides the abatement potential and abatement cost, we also explore the complex substitution nexus between desirable and undesirable outputs. The Morishima elasticity of substitution in Equation (7) measures how the relative price ratio responds to the change in intensity between pollutants and industrial value-added. A negative sign of Morishima elasticity reflects a trade-off relationship. By contrast, a

Table 4. Comparison with related studies.

Studies	Pollutant[a]	Method[b]	Period	Sample	Average abatement cost
Wang & Lall (2002)	COD	OLS	1994	1,500 Chinese industrial firms	Large firms: 582.3 CNY/ton Medium firms: 775.6 CNY/ton Small firms: 1,652.3 CNY/ton
Dasgupta *et al.* (2001)	Biochemical oxygen demand (BOD), COD, TSS	OLS	1994	260 Chinese firms	TSS: 4 $/ton COD: 20 $/ton BOD: 25 $/ton
Wang *et al.* (2015)	COD, NH_4	DEA	2009–2010	30 provinces in mainland China industrial sector	COD (2009): 69.26 CNY/kg NH_4 (2009): 1,646.22 CNY/kg COD (2010): 65.14 CNY/kg NH_4 (2010): 1,446.43 CNY/kg
Kumar & Managi (2011)	BOD, COD, SS	DDF + parametric	1996–1999	92 firms of Indian water-polluting industry	BOD: 160,000–520,000 Indian Rs/ton COD: 20,000–170,000 Indian Rs/ton SS: 150,000–550,000 Indian Rs/ton
Tang *et al.* (2016)	COD, TN, TP	DDF + parametric	2001–2010	26 provinces in mainland China agriculture sector	8,266 CNY/ton for COD; 25,560 CNY/ton for TN; 10,160 CNY/ton for TP
Present study	COD, NH_4	DDF + parametric	2003–2012	30 provinces in mainland China industrial sector	COD: 700 CNY/kg NH_4: 7,000 CNY/kg

[a]COD, BOD, TSS, NH_4, TN, and TP are chemical oxygen demand, biochemical oxygen demand, total suspended solids, ammonia nitrogen (NH_4), total nitrogen and total phosphorus, respectively.
[b]OLS, DDF and DEA refer to ordinary least squares, directional distance function and data envelopment analysis, respectively.

positive coefficient suggests 'win-win' opportunities because the reduction of the pollutant is associated with the expansion of industrial value-added (Kumar & Managi, 2011).

The result is presented in Figure 5 (Table 3 gives details). We found that the Morishima elasticity of COD is negative over time, which indicates that China would have to sacrifice industrial output to cut COD. However, the average Morishima elasticity of NH_4 is positive, which indicates that there exist 'win-win' opportunities for some provinces to control NH_4 emissions without any economic loss.

The Morishima elasticity of COD also exhibits an upward trend in terms of its absolute value, which suggests that it is getting more difficult and expensive to further reduce COD emissions. However, the Morishima elasticity of NH_4 does not show a clear trend and, instead, fluctuates over time.

Looking at Figure 6, we find it also consistent with the distribution of abatement costs. The developed provinces, like Guangdong, Shandong, Jiangsu, are associated with a negative Morishima elasticity. This means the reduction of COD and NH_4 in these areas is increasingly difficult and costly. In contrast, the developing provinces, like Qinghai, Gansu, Anhui, Chongqing, etc., are associated with a smaller negative score of Morishima elasticity for COD and a larger positive score for NH_4. This suggests that the abatement activity of industrial COD and NH_4 in these regions either is less costly or has the possibility to achieve a 'win-win' outcome.

5. Determinants of abatement cost

The great provincial disparity and time-varying trends of abatement costs further motivate us to explore their driving forces. In the light of previous literature, we account for the following possible factors.

1. **Pollutant intensity.** As our correlation tests show, pollutant intensity is strongly correlated with abatement cost, which is in line with the theory of the marginal abatement cost curve (Murty *et al*., 2007). A higher value of COD intensity means a 'higher pollution level' for one unit of economic output. Consequently, it is much easier and cheaper to reduce one unit of additional emission. Thus, we expect a negative nexus between the pollutant intensity and its abatement cost. The COD intensity is measured with the COD emission over industrial value added. Similarly, the NH_4 intensity is expressed as the NH_4 emission per unit of industrial value added.

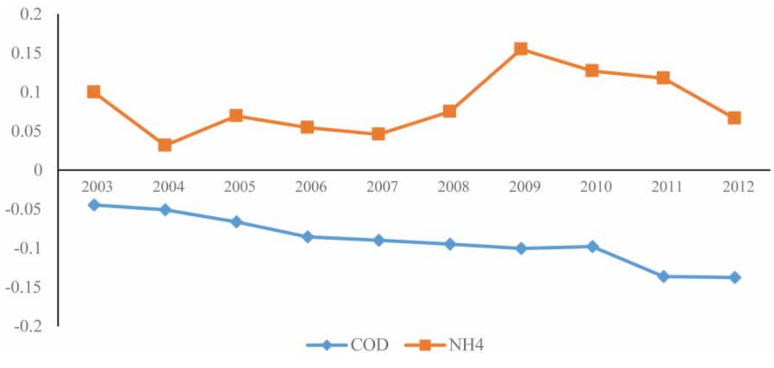

Fig. 5. Morishima elasticity of COD and NH_4 (2003–2012).

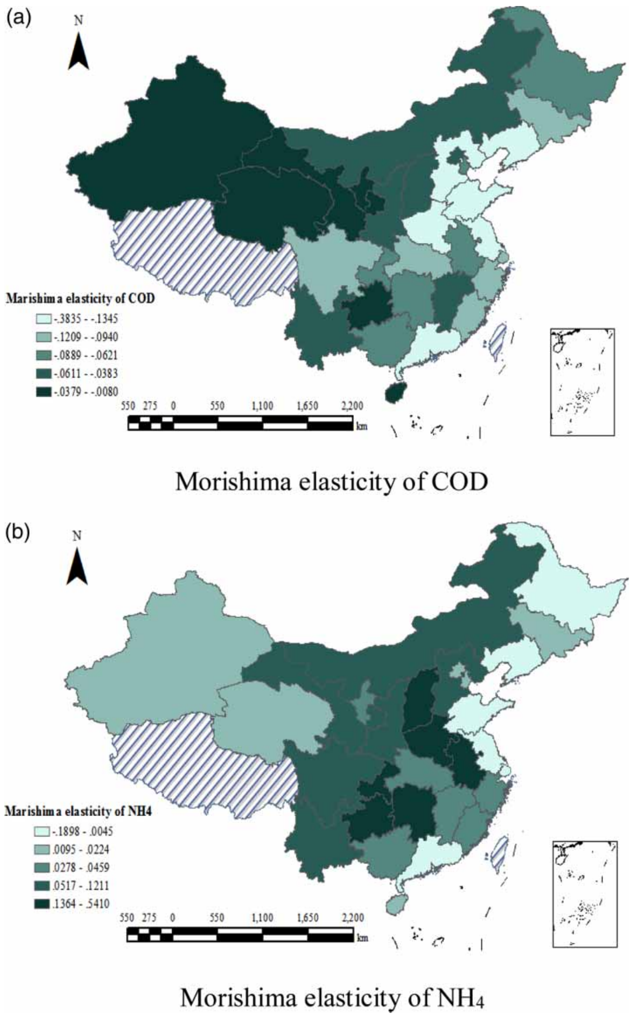

Fig. 6. Geographic distribution of Morishima elasticity of COD and NH_4 (2003–2012).

2. **Economic development level.** In order to control pollution, a decision-maker has to either switch their inputs to abatement activities, or reduce their output to reduce the undesirable by-products. In both cases, the pollution abatement activities will move the potential output frontier to a lower level. Thus, the abatement cost measures the opportunity cost when controlling pollution. One would expect that the developed provinces would suffer greater potential economic loss, and thus experience high abatement costs. In our case, the gross domestic product (GDP) per capita (*RGDP*) is adopted to indicate the economic development level. We also introduce its squared term to test the nonlinearity effect. In accordance with the Environmental Kuznets Curve hypothesis, the abatement cost may first experience a decline and then increase, which in turn shapes a U curve. In that case, the coefficient of *RGDP* is expected to be negative while the squared term's coefficient is positive.
3. **The capital intensity.** The capital-labor ratio is a good indicator to measure the capital intensity. It can be used to proxy whether the industrial sector is capital-intensive or labor-intensive. Capital is a

complement to intermediate materials and energy in the short run (Griffin & Gregory, 1976). The province with greater capital usage per unit of labor is expected to demand more intermediate inputs and energy resources for one unit of economic output, which leads to worse environmental quality (Cole *et al.*, 2008). We expect a positive sign for capital intensity.

4. **Policy dummy.** Environmental policy is regarded as the effective way to attain environmental goals, like the cap-and-trade system (Du *et al.*, 2016). Three important public policies were adopted during the period of our sample. In 2006, the government set a mandatory reduction target for COD emission. In 2011, a mandatory target for NH_4 abatement was introduced and implemented. The tightening regulation of COD and NH_4 emissions may have led to the rise of abatement costs. Moreover, the government implemented an economic stimulus program in 2009 to boost growth in the context of the global economic recession. All three policies also provide us with a chance to examine their possible impacts on abatement costs. Three dummies (*Dummy2006*, *Dummy2009* and *Dummy2011*) are introduced to examine the policy effects in 2006, 2009 and 2011. The variable *Dummy2006* equals 1 for year 2006–2012; otherwise, it equals zero. The same setting is used for *Dummy2009* and *Dummy2011*.

In addition, we introduce cross-terms between year dummies and control variables to explore the mechanisms. We assume that the policy interventions may affect the abatement cost through the change of pollution intensity, the level of economic activity and capital intensity. The statistical descriptions of all the regression variables are summarized in Table 5.

In order to examine the determinants of abatement cost of COD and identify the active mechanism, an empirical econometric model is specified below.

$$\begin{aligned} ln(q_1)_{i,t} = {} & \alpha_0 + \alpha_1 ln(q_1)_{i,t-1} + \alpha_2 ln(CODinten)_{i,t} + \alpha_3 RGDP_{i,t} + \alpha_4 \left(\frac{K}{L}\right)_{i,t} + \alpha_5 Dummy2006_{i,t} \\ & + \alpha_6 Dummy2006_{i,t} \times ln(CODinten)_{i,t} + \alpha_7 Dummy2006_{i,t} \times RGDP_{i,t} \\ & + \alpha_8 Dummy2006_{i,t} \times \left(\frac{K}{L}\right)_{i,t} + \alpha_9 Dummy2009_{i,t} + \alpha_{10} Dummy2009_{i,t} \\ & \times ln(CODinten)_{i,t} + \alpha_{11} Dummy2009_{i,t} \times RGDP_{i,t} + \alpha_{12} Dummy2009_{i,t} \times \left(\frac{K}{L}\right)_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

Table 5. Statistic description of regression variables.

Variables	Unit	Mean	Std. Dev.	Min	Max
$ln(q_1)$	10^4 Yuan/ton	3.879	0.715	1.872	6.851
$ln(q_2)$	10^4 Yuan/ton	5.363	1.548	0.262	10.110
Ln(CODinten)	ton/10^8 Yuan	3.993	1.201	0.573	7.727
Ln(NH$_4$inten)	ton/10^8 Yuan	1.314	1.228	−1.949	4.580
RGDP	10^4 Yuan	0.823	0.435	0.241	2.449
K/L	10^4 Yuan/person	18.906	8.816	7.479	51.808
Dummy2006	–	0.702	0.458	0	1
Dummy2009	–	0.387	0.488	0	1
Dummy2011	–	0.184	0.388	0	1

In Equation (8), a one-year lagged term for abatement cost is included to reduce the endogeneity problem resulting from the omitted variables. ε_{it} is the error term.

Equation (9) is used to examine the determinants of NH_4's abatement cost. The *Dummy2006* is replaced by *Dummy2011* because the binding mitigation target of NH_4 was implemented at the beginning of the 12th FYP (2011).

$$\begin{aligned} ln(q_2)_{i,t} = {} & \alpha_0 + \alpha_1 ln(q_2)_{i,t-1} + \alpha_2 ln(ANinten)_{i,t} + \alpha_3 RGDP_{i,t} + \alpha_4 \left(\frac{K}{L}\right)_{i,t} + \alpha_5 Dummy2011_{i,t} \\ & + \alpha_6 Dummy2011_{i,t} \times ln(ANinten)_{i,t} + \alpha_7 Dummy2011_{i,t} \times RGDP_{i,t} \\ & + \alpha_8 Dummy2011_{i,t} \times \left(\frac{K}{L}\right)_{i,t} + \alpha_9 Dummy2009_{i,t} + \alpha_{10} Dummy2009_{i,t} \\ & \times ln(ANinten)_{i,t} + \alpha_{11} Dummy2009_{i,t} \times RGDP_{i,t} + \alpha_{12} Dummy2009_{i,t} \times \left(\frac{K}{L}\right)_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{9}$$

The regression results for COD and NH_4 are listed in Tables 6 and 7, respectively. We first regress against all control variables and then add the policy dummy and its interaction terms. The Hausman test favors the fixed effect estimation. All continuous variables are expressed in log forms to avoid the heterogeneity problem.

In Table 6, the coefficient of the one-year lagged term of $ln(q_1)$ is significantly positive. It favors the 'path dependence' hypothesis that the present abatement cost is heavily determined by the historical

Table 6. Regression result on the determinants of COD's shadow price.

Variables	$ln(q_1)$ (log COD's shadow price)			
Lag 1 term of $ln(q_1)$	0.642*** (0.054)	0.586*** (0.057)	0.632*** (0.059)	0.592*** (0.060)
ln(CODinten)	−0.166*** (0.043)	−0.002 (0.066)	−0.151*** (0.052)	−0.001 (0.067)
RGDP	−1.498* (0.774)	−1.417* (0.793)	−1.544** (0.779)	−1.497* (0.790)
$RGDP^2$	0.529** (0.243)	0.606** (0.250)	0.522** (0.253)	0.583** (0.256)
K/L	0.017*** (0.005)	0.021*** (0.008)	0.026*** (0.007)	0.025*** (0.009)
Dummy2006		1.011*** (0.370)		1.232*** (0.400)
Dummy2006 × *ln(CODinten)*		−0.177*** (0.060)		−0.229*** (0.066)
Dummy2006 × *RGDP*		−0.150 (0.143)		−0.273* (0.155)
Dummy2006 × *(K/L)*		−0.004 (0.006)		0.001 (0.007)
Dummy2009			−0.029 (0.259)	−0.352 (0.281)
Dummy2009 × *ln(CODinten)*			0.040 (0.048)	0.105** (0.053)
Dummy2009 × *RGDP*			0.105 (0.130)	0.188 (0.136)
Dummy2009 × *(K/L)*			−0.010** (0.005)	−0.011** (0.005)
CONS.	2.557*** (0.591)	1.780*** (0.646)	2.407*** (0.616)	1.773*** (0.647)
Obs.	245	245	245	245
R^2	0.639	0.659	0.647	0.671
AIC	−26.408	−32.855	−24.371	−33.068

Standard errors in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. AIC refers to the Akaike Information Criterion which is a measure of the relative quality of statistical models for a given set of data.

Table 7. Regression result on the determinants of NH_4's shadow price.

Variables	$ln(q_2)$ (log NH_4's shadow price)			
Lag 1 term of $ln(q_2)$	0.337*** (0.053)	0.318*** (0.053)	0.328*** (0.052)	0.315*** (0.053)
$ln(NH_4inten)$	−0.168*** (0.055)	−0.148** (0.061)	−0.124* (0.069)	−0.121* (0.070)
RGDP	0.530 (1.234)	0.909 (1.354)	1.070 (1.268)	1.398 (1.384)
$RGDP^2$	−0.174 (0.402)	−0.215 (0.422)	−0.239 (0.430)	−0.273 (0.444)
K/L	−0.001 (0.009)	−0.002 (0.010)	0.016 (0.013)	0.015 (0.014)
Dummy2011		0.044 (0.325)		−0.041 (0.380)
Dummy2011 × $ln(NH_4inten)$		−0.292** (0.120)		−0.245* (0.145)
Dummy2006 × *RGDP*		−0.299 (0.261)		−0.289 (0.322)
Dummy2011 × *(K/L)*		0.018* (0.011)		0.019 (0.011)
Dummy2009			0.142 (0.292)	0.055 (0.342)
Dummy2009 × $ln(NH_4inten)$			−0.182** (0.085)	−0.106 (0.109)
Dummy2009 × *RGDP*			−0.078 (0.219)	0.076 (0.272)
Dummy2009 × *(K/L)*			−0.004 (0.009)	−0.008 (0.009)
CONS.	3.580*** (0.712)	3.382*** (0.799)	2.915*** (0.758)	2.752*** (0.843)
Obs.	245	245	245	245
R^2	0.309	0.329	0.335	0.347
AIC	261.200	261.738	259.654	263.141

Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

abatement cost. The COD intensity is found to be significantly negative, associated with the abatement cost of COD. It suggests that the abatement cost for a 'dirty' province (which emits more COD for one unit of industrial output) will be much cheaper. In contrast, the 'clean' province that has lower COD intensity is associated with higher abatement cost. In general, a 1% decrease of COD intensity will lead to a 0.15–0.17% increase in the abatement cost.

The negative sign of the *RGDP* and the positive sign of its squared term show a U-shaped relationship between the economic development level and COD's abatement cost. This seems consistent with the Environmental Kuznets Curve. The turning point is about 13,400 Yuan. This means that the abatement cost for the poor provinces whose *RGDP* is less than 13,400 Yuan will decline along with the abatement activities. On the contrary, further abatement activities will become more costly for the developed provinces, whose per capita GDP exceeds the turning point.

We also notice that the capital-labor ratio is an important factor. The significant positive coefficient is consistent with our expectation. It indicates that those provinces whose industrial composition is capital-intensive will have higher abatement costs. In general, a 1% increase of capital intensity will lead to a 0.017–0.026% increase in abatement cost.

The *Dummy2006* in Table 6 shows a significantly positive impact on the abatement cost. It shows that the COD mandatory abatement policy implemented in 2006 does increase the abatement cost. Among its interaction terms, only *Dummy2006* × *ln(CODinten)* is remarkable, while the other two are not significant. This suggests that COD regulatory policy generates an indirect impact on the abatement cost through the change of COD intensity. In other words, the marginal effect of the policy in the second column in Table 6 can be expressed as $d(\ln q_1)/d(dummy2006) = 1.011 - 0.177^{*}\ ln(CODinten)$. We can conclude that the COD mandatory abatement program that started in 2006 has two effects. On the one hand, it directly pushes up the abatement cost; on the other hand, it reduces the abatement cost through the change of COD intensity.

The direct impact of the economic stimulus program (*Dummy2009*) on the abatement cost is not significant, while it creates an indirect effect through the change of capital-labor ratio. Given its negative coefficient for the interaction term $Dummy2009 \times (K/L)$, it lowers the abatement cost after 2009 and the abatement cost becomes much lower for capital-intensive provinces.

Similarly, we report the regression result for NH_4's abatement cost in Table 7. Because the regulation of NH_4 emissions started in 2011, data is collected for only two years (2011 and 2012). We make the following observations. First, the coefficient of $ln(NH_4inten)$ is significantly negative, which is consistent with the COD case. This indicates that the province with higher NH_4 intensity is associated with a lower abatement cost to cut NH_4 emissions. Second, the economic development level and the capital-labor ratio have no significant effect on the NH_4 abatement cost. Third, the NH_4 emission reduction policy launched in 2011 does not affect the abatement cost directly. Instead, it has two indirect effects: it reduces the abatement cost through changing NH_4 intensity while increasing the abatement cost by changing capital intensity. Moreover, the impact of the economic stimulus program launched in 2009 is slight and insignificant.

6. Conclusion and policy implications

Using a parametric DDF approach, this paper simultaneously models the joint production of industrial value added and pollutant emissions. The abatement potential, abatement cost and Morishima elasticity of substitution for industrial COD and NH_4 are examined for the Chinese industrial sector during 2003–2012. The results suggest that the national industrial COD and NH_4 emissions can be further reduced by 13.18% and 13.27%, respectively, if inefficiency can be eliminated. This abatement activity is associated with opportunity costs, which should be taken into account. The average marginal cost to cut one unit of industrial COD is 710 Yuan/kg, and the average marginal cost to cut one unit of industrial NH_4 is 7,390 Yuan/kg. The abatement potential and cost exhibit similar trends during 2003–2012, during which we observe significant shocks in 2006 and 2010. Our results also demonstrate great regional disparity. The developed provinces are associated with expensive abatement costs while the developing regions are associated with greater abatement potential and lower costs.

The great heterogeneity among the provinces implies that it is not cost-effective to distribute the abatement target uniformly among different regions. In the developed provinces, it is much more expensive to mitigate COD and NH_4 than in the developing provinces. Thus, it would reduce the overall abatement cost to allocate more burdens to the developing provinces, where 'win-win' opportunities exist. There may be concern that this will lead to inequity for poor areas. However, a tradable permit market can deal with both efficiency and equity issues (Moore, 2015), i.e., the developed provinces can buy the abatement quotas from the developing regions, which will happen if and only if the trading price is lower than the abatement cost in rich areas and is higher than the abatement cost in poor areas. This trade will reduce the total transaction costs and achieve the overall emission-abatement target. Moreover, it also will improve efficiency in the developing areas, while trading will provide revenue or investment capital to the poorer areas. In short, the diversified abatement potential and abatement costs among provinces urgently call for the establishment of a national Emissions Trading System, which can assist China in reaching its environmental goals in a cost-effective way while balancing its regional development.

In addition, we notice a remarkable increase in abatement cost in 2006 and a significant drop in 2010. We infer that the binding targets for COD and NH_4 abatement at the beginning of the 11th FYP created a strong incentive for local decision-makers. This policy shock led to vast investment in pollution abatement. Consequently, we observe a sharp rise in marginal cost. In contrast, the massive economic stimulus program during the global financial crisis in 2009 may have allowed inefficient and pollution-intensive firms to survive or even expand. Another explanation is that the global crisis shifted the government's focus from reducing pollution to boosting the economy. In order to confirm our assumption, we ran a regression against the abatement cost of COD and NH_4. The empirical results suggest that 'the dirtier the emission, the cheaper the abatement cost' for both water pollutants. The results also demonstrate a U-shaped relationship between economic level and abatement cost of COD (which does not hold for NH_4). More importantly, we find that the mandatory reduction target for COD emissions in 2006 significantly affected the COD abatement cost through decreasing the COD intensity in production. The economic stimulus plan in 2009 affected the abatement costs through the change of pollution intensity and capital intensity. Moreover, we observe that the mandatory abatement for NH_4 emissions in 2011 affected the abatement cost through the decline of the NH_4 intensity in production. However, the 2009 economic stimulus plan had an insignificant effect on the cost of abatement.

Last but not least, a more comprehensive framework concerning the externality, the ecosystem, and the public health impacts of water pollution should be scrutinized based on the economic impact assessment. The other valuation methods, like the cost of illness approach or human capital approach, could also be conducted for a small river basin or a specific economic region using the firm or resident data. The information regarding abatement cost in most regulations and policy-making process is not the issue because most costs cannot be properly captured. In the present paper, the abatement cost of industrial water pollutants we assessed is focused on the opportunity cost, rather than the overall negative externality cost. Besides, a fair national emissions trading system for water pollutants especially on the allocation of water quotas and water environmental capacity is left for further studies.

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References

Aigner, D. J. & Chu, S. F. (1968). On estimating the industry production function. *The American Economic Review 58*(4), 826–839.

Bassi, N. (2014). Assessing potential of water rights and energy pricing in making groundwater use for irrigation sustainable in India. *Water Policy 16*(3), 442–453.

Chen, W. Y. (2017). Environmental externalities of urban river pollution and restoration: a hedonic analysis in Guangzhou (China). *Landscape and Urban Planning 157*, 170–179.

Christian-Smith, J., Cooley, H. & Gleick, P. H. (2012). Potential water savings associated with agricultural water efficiency improvements: a case study of California, USA. *Water Policy 14*(2), 194–213.

Chung, Y. H., Färe, R. & Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *Journal of Environmental Management 51*(3), 229–240.

Cole, M. A., Elliott, R. J. R. & Wu, S. (2008). Industrial activity and the environment in China: an industry-level analysis. *China Economic Review 19*(3), 393–408.

Dasgupta, S., Huq, M., Wheeler, D. & Zhang, C. (2001). Water pollution abatement by Chinese industry: cost estimates and policy implications. *Applied Economics 33*(4), 547–557.

Du, L., Hanley, A. & Wei, C. (2015). Marginal abatement costs of carbon dioxide emissions in China: a parametric analysis. *Environmental and Resource Economics 61*(2), 191–216.

Du, S., Hu, L. & Song, M. (2016). Production optimization considering environmental performance and preference in the cap-and-trade system. *Journal of Cleaner Production 112*(Part 2), 1600–1607.

Dwight, R. H., Fernandez, L. M., Baker, D. B., Semenza, J. C. & Olson, B. H. (2005). Estimating the economic burden from illnesses associated with recreational coastal water pollution – a case study in Orange County, California. *Journal of Environmental Management 76*(2), 95–103.

Ensink, J. H. J., Mahmood, T., van der Hoek, W., Raschid-Sally, L. & Amerasinghe, F. P. (2004). A nationwide assessment of wastewater use in Pakistan: an obscure activity or a vitally important one? *Water Policy 6*(3), 197–206.

Färe, R. & Grosskopf, S. (2010). Directional distance functions and slacks-based measures of efficiency. *European Journal of Operational Research 200*(1), 320–322.

Färe, R., Grosskopf, S., Lovell, C. A. K. & Yaisawarng, S. (1993). Derivation of shadow prices for undesirable outputs: a distance function approach. *The Review of Economics and Statistics 75*(2), 374–380.

Färe, R., Grosskopf, S., Noh, D.-W. & Weber, W. (2005). Characteristics of a polluting technology: theory and practice. *Journal of Econometrics 126*(2), 469–492.

Färe, R., Grosskopf, S. & Weber, W. L. (2006). Shadow prices and pollution costs in U.S. agriculture. *Ecological Economics 56*(1), 89–103.

Färe, R., Martins-Filho, C. & Vardanyan, M. (2010). On functional form representation of multi-output production technologies. *Journal of Productivity Analysis 33*(2), 81–96.

Griffin, J. M. & Gregory, P. R. (1976). An intercountry translog model of energy substitution responses. *The American Economic Review 66*(5), 845–857.

Guignet, D. (2012). The impacts of pollution and exposure pathways on home values: a stated preference analysis. *Ecological Economics 82*, 53–63.

Hongyun, H. & Liange, Z. (2007). Chinese agricultural water resource utilization: problems and challenges. *Water Policy 9*(S1), 11–28.

Hu, Y. & Cheng, H. (2013). Water pollution during China's industrial transition. *Environmental Development 8*, 57–73.

Jawahar, P. & Ringler, C. (2009). Water quality and food safety: a review and discussion of risks. *Water Policy 11*(6), 680–695.

Kumar, S. & Managi, S. (2011). Non-separability and substitutability among water pollutants: evidence from India. *Environment and Development Economics 16*(06), 709–733.

Marklund, P.-O. & Samakovlis, E. (2007). What is driving the EU burden-sharing agreement: efficiency or equity? *Journal of Environmental Management 85*(2), 317–329.

MEP (2008). *Report on the State of the Environment in China*. Ministry of Environmental Protection of China, Beijing, pp. 1–40.

MEP (2014). *Report on the State of the Environment in China*. Ministry of Environmental Protection of China, Beijing, pp. 1–40.

Moore, S. M. (2015). The development of water markets in China: progress, peril, and prospects. *Water Policy 17*(2), 253–267.

Murty, M., Kumar, S. & Dhavala, K. (2007). Measuring environmental efficiency of industry: a case study of thermal power generation in India. *Environmental and Resource Economics 38*(1), 31–50.

National Bureau of Statistics (2014). *China Statistical Yearbook.* China Statistics Press, Beijing.

Ng, T. L. (2015). Cost comparison of seawater for toilet flushing and wastewater recycling. *Water Policy 17*(1), 83–97.

Price, L., Levine, M. D., Zhou, N., Fridley, D., Aden, N., Lu, H., McNeil, M., Zheng, N., Qin, Y. & Yowargana, P. (2011). Assessment of China's energy-saving and emission-reduction accomplishments and opportunities during the 11th Five Year Plan. *Energy Policy 39*(4), 2165–2178.

Song, M., An, Q., Zhang, W., Wang, Z. & Wu, J. (2012). Environmental efficiency evaluation based on data envelopment analysis: a review. *Renewable and Sustainable Energy Reviews 16*(7), 4465–4469.

Song, M., Song, Y., An, Q. & Yu, H. (2013). Review of environmental efficiency and its influencing factors in China: 1998–2009. *Renewable and Sustainable Energy Reviews 20*, 8–14.

Stonich, S. C. (1998). Political ecology of tourism. *Annals of Tourism Research 25*(1), 25–54.

Tang, K., Gong, C. & Wang, D. (2016). Reduction potential, shadow prices, and pollution costs of agricultural pollutants in China. *Science of the Total Environment 541*, 42–50.

Wang, H. & Lall, S. (2002). Valuing water for Chinese industries: a marginal productivity analysis. *Applied Economics 34*(6), 759–765.

Wang, Q. & Yang, Z. (2016). Industrial water pollution, water environment treatment, and health risks in China. *Environmental Pollution 218*, 358–365.

Wang, Y., Bian, Y. & Xu, H. (2015). Water use efficiency and related pollutants' abatement costs of regional industrial systems in China: a slacks-based measure approach. *Journal of Cleaner Production 101*, 301–310.

Wei, C., Ni, J. & Du, L. (2012). Regional allocation of carbon dioxide abatement in China. *China Economic Review 23*(3), 552–565.

Wei, C., Löschel, A. & Liu, B. (2015). Energy-saving and emission-abatement potential of Chinese coal-fired power enterprise: a non-parametric analysis. *Energy Economics 49*, 33–43.

World Bank (2007). *Water Pollution Emergencies in China: Prevention and Response.* World Bank, Washington, DC.

Wu, L., Qi, T., Li, D., Yang, H., Liu, G., Ma, X.-y. & Gao, J. -E. (2015). Current status, problems and control strategies of water resources pollution in China. *Water Policy 17*(3), 423–440.

Xie, H., Shen, M. & Wei, C. (2016). Technical efficiency, shadow price and substitutability of Chinese industrial SO_2 emissions: a parametric approach. *Journal of Cleaner Production 112*, 1386–1394.

Zhang, J., Mauzerall, D. L., Zhu, T., Liang, S., Ezzati, M. & Remais, J. V. (2010). Environmental health in China: progress towards clean air and safe water. *The Lancet 375*(9720), 1110–1119.

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