A cost-benefit analysis of the environmental taxation policy in China: A frontier analysis-based environmentally extended input-output optimization method

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Abstract: China's high-speed economic development and reliance on over-consumption of natural resources has led to serious environmental pollution. Environmental taxation is seen as an effective economic tool to help mitigate air pollution. In order to assess the effects of different scenarios of environmental taxation policies, we propose a frontier based environmentally extended input-output optimization model with explicit emission abatement sectors to reflect the inputs and benefits of abatement. Frontier analysis ensures policy scenarios are assessed under the same technical efficiency benchmark, while input-output analysis depicts the wide range of economic transactions among sectors of an economy. Four scenarios are considered in this study, which are increasing specific tax rates of SO_2, NO_x, and soot & dust separately and increasing all three tax rates simultaneously. Our estimation results show that: raising tax rates of SO_2, NO_x, and soot & dust simultaneously would have the highest emission reduction effects, with the SO_2 tax rate making the greatest contribution to emission reduction. Raising the soot & dust tax rate is the most environmentally friendly strategy due to its highest abatement welfare through avoided health costs. The combination of frontier analysis and input-output analysis provides policy makers a comprehensive and sectoral approach to assess costs and benefits of environmental taxation.

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Key words: environmental tax; environmentally extended input-output table; optimization model; frontier analysis; DEA; air pollution

1. Introduction

China's high-speed economic development during the last four decades has relied on an over-consumption of energy and material, which has led to serious environmental pollution. China's sulfur dioxide (SO_2), nitrogen oxides (NO_x), and soot & dust emissions rank among the highest in the world (Wang et al., 2018). Moreover, excessive air pollution has caused a series of local environmental problems, such as haze and fog, in China's major cities (Liang et al., 2016). Facing multiple severe international and domestic environmental and public health challenges, environmental improvement and sustainable development have been stressed as China's primary development targets for the last decade or so (Cao et al., 2010). Market-based policy instruments have become an increasingly popular approach to address environmental issues since the 1980s (Mansfield, 2006). Environmental taxation, as a primary market-based policy instrument, has been widely promoted in developed countries (Chiroleu-Assouline & Fodha, 2014). Recently, a new environmental taxation policy, the "Environmental Protection Tax Law," was introduced in China at the beginning of 2018, which contains a SO_2 tax, a NO_x tax and a soot & dust tax. As a consequence, the pollution fees policy was replaced. However, according to Nordhaus (1982), policies which aim at reducing greenhouse gas emissions can only be effective through economic mechanisms. Specifically, pollution abatement, which is determined by environmental policies, will affect level and costs of production. Thus, in addition to environmental outcomes there are economic implications. For example, Ahmed & Ahmed (2018) show that strict environmental policies would impede the GDP growth rate in China. In other words, there are trade-offs between economic costs and environmental benefits of abatement activities. We quantify economic costs in terms of GDP loss and environmental benefits as a reduction in health costs due to the emission reduction associated with an increase of environmental tax rates.

Given that, contrary to public statements, general development strategies in China are heavily relying on economic growth, pollution reduction requires a substantial increase of environmental efficiency. In other words, effects of environmental policies do not only comprise the 'direct' impacts of the policy itself, but also lead to changes in efficiency caused by the policy. Thus, an assessment of effects of environmental policies requires to eliminate the impacts of efficiency change and compare different policy scenarios against an efficiency benchmark. An environmental efficiency frontier offers efficient solutions involved with the objective of optimizing economic goals as well as environmental goals (Wu et al., 2018). As shown in the literature (Cook et al., 2010), data envelopment analysis (DEA) helps to estimate the environmental efficiency frontier and to identify best practices of decision making units (sectors, in this study). In this study, raising environmental efficiency stands for producing more industrial outputs with less primary inputs under the current level of emission abatement. Compared with traditional efficiency, environmental efficiency takes environmental as well as economic aspects into consideration (Mahlberg & Luptacik, 2014). Moreover, environmental policy affects goods and services throughout upstream supply chains (Xing et al., 2018). Input-output (IO) analysis allows the quantification of 'embodied' economic input and output relations of economic sectors in an economy capturing the entire supply chain from production to consumption (Ogarenko & Hubacek, 2013). The underlying IO tables provide a network of intermediate flows, primary inputs and final outputs among production sectors. Environmentally extended input-output (EEIO) models add environmental flows, i.e. resource consumption, environmental pressures or environmental impacts to the economic IO model. Thus, in order to analyze the cost-benefit effect of environmental policy across various sectors under the same technical efficiency benchmark, we combine frontier analysis with an EEIO model to measure environmental efficiency.

In this study, we establish an EEIO table by introducing emission abatement sectors to reflect the inputs and benefits of air pollution abatement. Then, an optimization model is developed by combining the Leontief IO model and the DEA based frontier analysis to measure the environmental efficiency. The method is applied to evaluate the trade-offs between economic costs and environmental benefits of the environmental taxation policy in China. In this paper, we consider three air pollutants: SO_2, NO_x, and soot & dust.

The main contribution of this study is that we extend the conventional IO table by introducing emission abatement sectors to reflect the inputs and benefits of abatement. Moreover, we propose an optimization model that combines the Leontief IO model and the DEA based frontier analysis, so that the effects of each policy scenario could be simulated under a consistent technical efficiency benchmark and under the inter-sectoral input and output constrains. Not only environmental benefits but economic costs, including emission abatement costs, could be identified through this model. The application of the model provides comprehensive assessment on the trade-offs between the abatement and production of different economic sectors, considering both environmental benefits and economic costs. This framework provides policy makers with a way to formulate environmental taxation policy taking into account emission reduction effects as well as the trade-offs between the environmental benefits and economic costs of abatement.

2. Methodology

2.1 Overview

Methods of impacts of environmental or energy policy on the economy or environment are various (Wang et al., 2016), including computable general equilibrium analysis (Yahoo & Othman, 2017), life cycle analysis (Lu et al., 2017), statistical and econometric analysis (Tan et al., 2018), and frontier analysis (Li & Lin, 2016). Frontier analysis ensures that the policy scenarios are assessed without the impacts of technical inefficiency. DEA is a popular frontier approach in the field of energy and environmental efficiency at the macro level (Wang et al., 2013; Zhang & Chen, 2018). Using DEA, Vlontzos et al. (2014) calculated the energy and environmental efficiency of agriculture in the EU. Wu et al. (2016) evaluated the environmental efficiency of 30 provinces and 8 regions in China. Xian et al. (2018) estimated the gap between carbon emission reduction and its target for China's power industry with consideration of carbon productivity change. However, DEA cannot depict the wide range of economic transactions among sectors of an economy, therefore EEIO analysis is used to evaluate the effects of environmental policy considering complex supply chains involving all sectors of an economy.

There are numerous studies using IO analysis to evaluate policies, technical change or consumption choices and their effects on regional spillover (Fang et al., 2019), or effects on a wide range of economic, social and environmental impacts including energy consumption (Guo et al., 2018), water consumption (Serrano & Valbuena, 2017), carbon emissions (Liu & Liang, 2017), PM2.5 (Meng et al., 2015), heavy metal pollution (Liang et al., 2015), biodiversity (Lenzen et al., 2012), and trade networks (Zhang et al., 2016).

For the purpose of evaluating the effects of environmental policy at the sector level, several studies have combined DEA and EEIO model and applied it to measure environmental efficiency or ecological efficiency (Wang et al., 2019), and estimated the potential of carbon emission reduction (Fu et al., 2017). Specifically, Munksgaard et al. (2005) aggregated different environmental effects into a single index to measure environmental pressure of consumption. Luptáčik and Böhm (2010) calculated the efficiency of a multi-sector economic system. Mahlberg and Luptacik (2014) measured eco-efficiency and eco-productivity change in Austria. Fu et al. (2017) assessed the carbon intensity reduction related to industrial shifts in China. Xing et al. (2018) analyzed the environmental impacts of economic activities. However, the trade-offs between environmental benefits and economic costs have seldom been analyzed in these studies. By using DEA-based frontier analysis and EEIO analysis, this study aims to evaluate the impacts of environmental policy under the same technical efficiency benchmark and the input-output supply chain, taking environmental benefits and economic costs into consideration.

2.2 Environmentally extended IO table

Using an IO table and environmental data, an environmentally extended IO table can be established for China. This setup is the foundation of the optimization model shown in section 2.3. The setup procedure is listed as follows. An intuitive description of the process is presented in Figure 1.

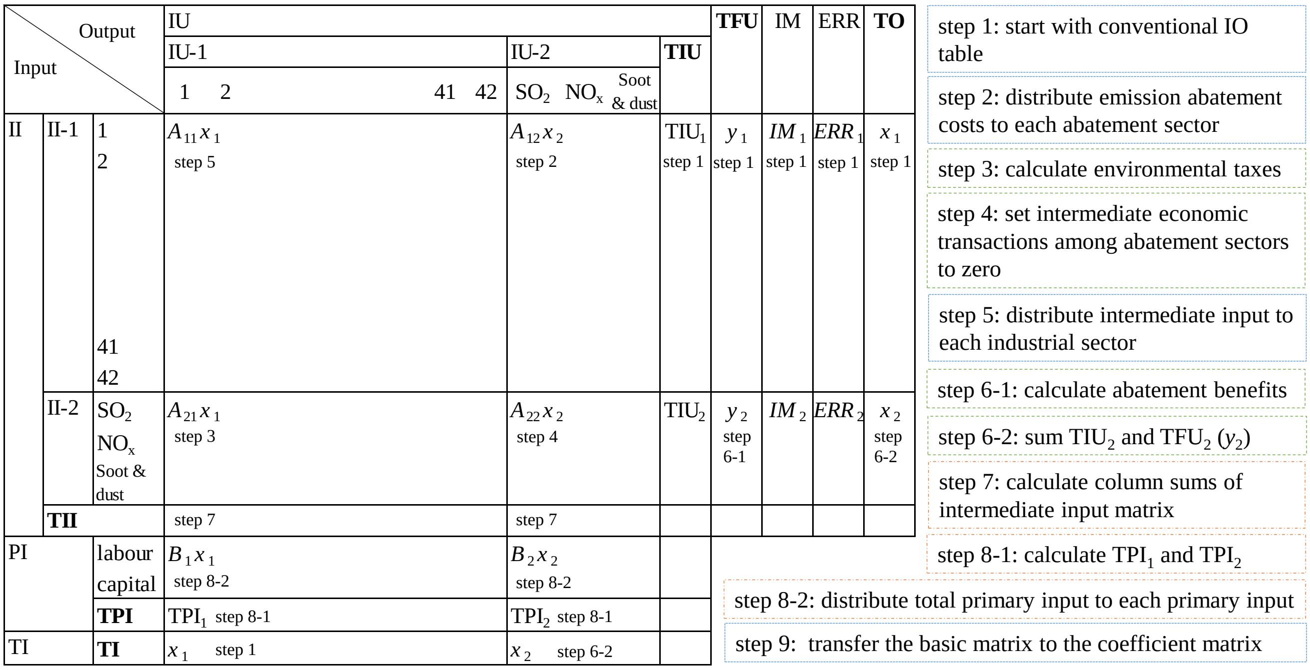

Figure 1 Construction steps of the environmentally extended IO table. II and TII represents intermediate input and total intermediate input, respectively. PI, TPI, and TI represents primary input, total primary input, and total input, respectively. IU and TIU represents intermediate use and total intermediate use, respectively. TFU, IM, ERR, and TO represents total final use, imports, errors, and total output, respectively. Subscripts 1 and 2 refer to economic sectors and abatement sectors, respectively. Sectors and corresponding codes are listed in Table S3. Boxes colored in blue, green,

and orange respectively represent steps related with production sectors, abatement sectors, and primary inputs.

STEP 1: Start with conventional IO table (TO_1, TFU_1, IM_1, ERR_1)

Given that the quantification of environmental values in this study will not affect the existing production scale, environmental extension has no influence on total intermediate use, final use, imports, errors and total outputs in economic sectors. In other words, x_1, y_1, IM_1 and ERR_1 are kept the same data as the conventional IO table.

STEP 2: Distribute emission abatement costs to each abatement sector ($A_{12}x_1$)

The dimensions of the intermediate input matrix in the 2012 conventional Chinese IO table are 42×42. They expand to 45×45 in our environmentally extended IO table, adding three columns and three rows for the SO_2, NO_x and soot & dust abatement sectors. The intermediate input matrix from each economic sector to each emission abatement sector is represented by abatement costs. Then we distribute emission abatement costs of economic sectors to each abatement sector by the emission proportion.

STEP 3: Calculate environmental taxes ($A_{21}x_2$)

Environmental taxes are calculated by the products of emission equivalents and environmental tax rates so that intermediate inputs (also known as emission rights) from abatement sectors to economic sectors can be valued in monetary units.

STEP 4: Set intermediate economic transactions among abatement sectors to zero ($A_{22}x_2$)

$A_{22}x_2$ is the matrix showing intermediate economic transactions among abatement sectors. Given that pollution control is achieved by abatement facilities of economic sectors and environmental taxes are levied at economic sectors, abatement costs and environmental taxes related to secondary emission during abatement process are already included in economic sectors in STEP 2 and STEP 3. Additionally, theoretical foundation and ratio of separating emissions of abatement sectors from economic sectors are scarce. Therefore, we assume there are no intermediate economic transactions among abatement sectors and set $A_{22}x_2$ to zero.

STEP 5: Distribute intermediate input to each economic sector ($A_{11}x_1$)

Assuming that the intermediate input proportions of each row are constant, the A_{11}-matrix in the extended IO table is calculated based on the difference between total intermediate use and the row sum of $A_{12}x_2$ for each sector.

STEP 6: Calculate abatement benefits (y_2) and environmental value (x_2)

The excessive emission causes a series of environmental issues, and leads to severe health costs as well. Consequently, emission abatements contribute to avoiding health costs through emission reduction. In view of this effect, we use the prevented health costs to measure abatement benefit (y_2). According to the World Bank (2007), health costs, measured in percentage of GDP, can be explained as the monetary value of emission damage or willingness to pay for emission abatement. Thus, like previous articles (e.g. Enkhtsolmon et al., 2016; Croitoru & Sarraf, 2017; Maji et al., 2017), we use the concept of health costs to evaluate the abatement benefits of emission reduction. More specifically, we first multiply the health costs by GDP to assess the total health damage related with the actual emission volume. Then, we calculate the damage per unit of emission through dividing the total health damage by the actual emission volume. At last, the abatement benefits are obtained through multiplying emission reduction by the damage per unit of emission. The volume of emission reduction is quantified based on the government proposed emission reduction target[†]. In addition, the total outputs of abatement sectors can be interpreted as the costs of

[†] Data sources: the 12th Five-year Plan for Prevention and Control of Air Pollution in Key Areas comes from the Ministry of Ecology and Environment of China, while the 13th Five-year Plan for Ecological and Environmental Protection comes from the State Council of China.

emission discharge (environmental taxes) and the benefits of emission abatement (abatement benefits). Thus, environmental values (x_2) are measured by the sum of total intermediate use of abatement sectors (TIU_2) and abatement benefits (y_2).

STEP 7: Calculate column sums of intermediate input matrix

The total intermediate input can be calculated as the sum of all elements in each column.

STEP 8: Distribute total primary input to each primary input (B_1x_1 and B_2x_2)

Total input minus total intermediate input leaves total primary input. Since the total input equals total output and the total output in the EEIO table is larger than that in the conventional IO table with environmental value taken into account, the total input in the EEIO table will be larger as well. Assuming that the primary input proportion is unchanged after the environmental extension, the total primary input of economic sectors can be distributed to each primary input. Moreover, because the primary input proportion of abatement sectors is unavailable and given that emission abatement is involved in productive processes, the total primary input of each abatement sector can be distributed to each primary input according to the average proportion of economic sectors.

STEP 9: Calculate the coefficient matrix (A_{11}, A_{12}, A_{21}, A_{22}, B_1, B_2)

To match the optimization model, all elements in intermediate and primary input matrixes must be transformed to coefficient form by dividing them by total output.

2.3 Environmentally extended IO optimization model based on frontier analysis

In this study, we use the IO table as a data source; for mathematical equations, we draw on Mahlberg and Luptacik (2014). An environmentally extended IO optimization model based on frontier analysis is extended from the conventional Leontief IO model by adding environmental values, which include costs for air pollution (environmental taxes) and prevented health costs of abatement (abatement benefits), with the frontier of DEA for optimization. The famous extended

Leontief IO model (Leontief, 1970; Miller & Blair, 2009; Mahlberg & Luptacik, 2014) improve the standard IO model by taking pollution generation and abatement activities into account, which can be described as:

$$\begin{bmatrix} I - A_{11} & -A_{12} \\ I - A_{21} & -A_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \geq \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} B_1 & B_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq z \tag{2}$$

The following notation is used in model (1): A_{11} is the $n \times n$ intermediate input coefficient matrix, showing the input of economic sector *i* per unit of output of economic sector *j*; A_{12} is the $n \times k$ intermediate input coefficient matrix, showing the input of economic sector *i* per unit of output of abatement sector *k* (SO_2 and NO_x, as well as soot & dust); A_{21} is the $k \times n$ intermediate input coefficient matrix, representing the three types of environmental taxes (sulfur tax, nitrogen tax, and soot & dust tax) of economic sector *j* per unit of output of economic sector *j*; and A_{22} is the $k \times k$ intermediate input coefficient matrix, representing the environmental taxes of abatement sector *k* per unit of output of abatement sector *k*. Therefore, in this way, the entire intermediate input coefficient matrix is separated into four sections (i.e. A_{11}, A_{12}, A_{21}, and A_{22}). y_1 is the $n \times 1$ final use vector of production sectors, containing total final consumption expenditures, gross capital formation and exports; y_2 is the $k \times 1$ final use vector of abatement sectors, which stands for prevented emissions through abatement. x_1 is the $n \times 1$ total output vector of economic sectors, which stands for the gross industrial output of economic sector *i*; x_2 is the $k \times 1$ total output vector of abatement sectors, calculated by the sum of environmental taxes (A_{21}) and abatement benefits (y_2), representing the environmental value. *I* is the identity matrix.

The factors in model (2) are listed below. B_1 is the $m \times n$ primary input coefficient matrix of economic sectors, which represents the primary inputs of economic sector *j* per unit of output of production sector *j*; B_2 is the $m \times k$ primary input coefficient matrix of abatement sectors, showing the primary inputs of abatement sector *k* per unit of output of abatement sector *k*. *z* is the $m \times 1$ total available primary input vector, which are valued in monetary units. In our study, *n* stands for the number of economic sectors (*n* = 1, 2, …, 42), *k* stands for the number of air pollution abatement sectors (*k* = 1, 2, 3), and *m* stands for the number of primary inputs (*m* = 1, 2).

Model (1) and (2) are rewritten as follows to match the Chinese IO table, which has IM and ERR representing imports and errors (balance item), respectively.

$$\begin{bmatrix} I - A_{11} & -A_{12} \\ I - A_{21} & -A_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} IM_1 & -ERR_1 \\ IM_2 & -ERR_2 \end{bmatrix} \geq \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} B_1 & B_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq z \tag{4}$$

The economic sectors and the abatement sectors are distinguished by subscripts 1 and 2. Furthermore, models (3) and (4) can be expanded in the following way.

$$x_1 - A_{11}x_1 - A_{12}x_2 + IM_1 - ERR_1 \geq y_1 \tag{5}$$

$$x_2 - A_{21}x_1 - A_{22}x_2 + IM_2 - ERR_2 \geq y_2 \tag{6}$$

$$B_1x_1 + B_2x_2 \leq z \tag{7}$$

Equations (5) and (6) describe the constraint that the total amount of output (import involved) must satisfy the needs of intermediate use and final use of both economic sectors and abatement sectors. In addition, equation (7) shows the restriction of primary inputs.

To compare the results of different policy scenarios, we must exclude the impact of different environmental efficiencies under different scenarios and ensure that the changes in the results are derived only from policy adjustments. To compare the influence of environmental policy and analyze the trade-offs between economic costs and environmental benefits, the concept of the environmental efficiency frontier arises for the economy. Consequently, it is necessary to measure environmental efficiency by means of an environmental efficiency frontier that considers the economy and the environment simultaneously.

Therefore, we combine the optimization method with the environmentally extended IO model. The efficiency gap can be obtained through the distances between observations and the frontiers. Additionally, observations and frontiers can be interpreted as real DMUs describing the actual performance of the economy and virtual DMUs defining the improved potential, respectively. Furthermore, the non-oriented proportional measure is provided through defining the direction vectors for net outputs of production sectors and primary inputs equal to the exogenously observed final demand and the exogenously observed available inputs, respectively. With a special case assuming constant returns to scale[‡], an environmentally extended IO optimization model based on frontier analysis is established in model (8). This model is a radial measurement since the primary inputs and the total outputs of production sectors are proportionally reduced and enlarged simultaneously. The amounts of products of decision-making units (DMUs, also known as sectors in this paper, including 42 economic sectors and 3 emission abatement sectors) on the environmental efficiency frontier cannot be improved without increasing at least one unit of input or decreasing at least one unit of primary input. In this study, 42 products of corresponding economic sectors acted as desirable outputs, and 3 pollutants of emission abatement sectors acted as undesirable outputs.

$$
\begin{aligned}
& \omega\ (z^0, y_1^0, y_2^0) = \max_{x_1, x_2, \delta} \delta \\
& s.t. \quad x_1 - A_{11}x_1 - A_{12}x_2 + IM_1 - ERR_1 \geq (1+\delta) y_1^0 \\
& \qquad\ \ x_2 - A_{21}x_1 - A_{22}x_2 + IM_2 - ERR_2 \geq y_2^0 \\
& \qquad\ \ B_1 x_1 + B_2 x_2 \leq (1-\delta) z^0 \\
& \qquad\ \ x_1, x_2 \geq 0, \delta \text{ free}
\end{aligned}
\tag{8}
$$

[‡] Production possibility set (PPS) of the conventional constant returns to scale DEA model (CCR) is shown as: $\text{PPS}_{\text{CCR}} = \{(x, y) \mid \lambda X^{\text{T}} \leq x, \lambda Y^{\text{T}} \geq y, \lambda \geq 0\}$, where x, y, and λ indicate inputs, outputs, and intensity variables, respectively.

where the notions with superscript 0 are exogenous variables; both ω and δ represent the environmental inefficiency scores of the economy systems, showing the improved potential that primary inputs could be proportionally reduced and final uses of production sectors could be proportionally increased to satisfy the exogenously given prevented emissions through abatement. $\omega = 0$ and $\delta = 0$ indicate an environmentally efficient economy, while $\omega > 0$ and $\delta > 0$ indicate an environmentally inefficient economy. Using the environmentally extended IO table, the extended IO optimization model can alternatively be formulated as a linear programming problem by maximizing environmental inefficiency score given the optimized primary inputs of economic and abatement sectors not higher than the levels of the currently available primary input quantities (z^0) and the optimized final use not lower than the levels of observed final use ($y_1{}^0$). Based on the sector level, the model offers an optimal environmental efficiency solution, which can be interpreted as simultaneously maximizing the desirable outputs and minimizing the primary inputs given the targets of emission reduction realized.

2.4 Data sources

The latest national-level Chinese IO table is in 2012 issued by the Department of National Economic Accounting in the National Bureau of Statistics of China[§]. It has two versions, which are a 42-sector version and a 139-sector version. However, the environmental data, including emissions and their abatement costs, are highly aggregated. Moreover, abatement costs refer to the running costs of the abatement facilities, including energy consumption, equipment depreciation, equipment maintenance, staff wages, management fees, pharmacy fees and other expenses associated with the operation of the facility. Because there are no reference data or additional information for disaggregating each part of the above abatement costs, we choose the 42-sector version in order to avoid the inaccuracy and uncertainty in disaggregating the abatement costs. Although Wang (2017) and Wang et al. (2017) have made great contribution to developing a multi-regional IO laboratory

[§] Input-output Table of China 2012.

for China with time series extended to 2015, we evaluate the effects of environmental taxation policy at the national level using the aforementioned Chinese 2012 IO table, given that data of sectoral abatement costs associated with abatement facilities of each province are unavailable and there would exist substantial uncertainty when allocating the data at the national level to the provincial level without any additional data.

Our model takes the two most important primary inputs into account, which are compensation of employees for labor input and depreciation of fixed assets for capital input. As for total available primary inputs (z), the former (labor) is represented by the ratio of the total employees and the total economically active population[**], and the latter (capital) is calculated by fixed assets' original cost in 2011[††] with depreciation (Chen, 2014). The detailed data sources are shown in Table S1.

Because our model is based on an environmentally extended IO model, data on the environment are required. To settle the inconsistency of sector classifications from different data sources, total energy consumption proportions of the 42 sectors are used, which are available from Department of Energy Statistics of National Bureau of Statistics China[‡‡]. Abatement costs and emissions are derived from Department of Industry Statistics of National Bureau of Statistics China[§§]. Given that the negative impacts on environment are likely to differ by different pollutants, the same emission loads of different pollutants will have different environmental effects. Therefore, according to the level of negative effects on environment and public health, we transfer the physical unit (kg) of emission to equivalent unit by using the "pollutant equivalent". On the basis of China's Ministry of Environmental Protection, the pollutant equivalent of SO_2, NO_x, and soot & dust is 0.95, 0.95 and 2.18, respectively. While environmental tax rates are obtained from government work reports. Moreover, according to the World Bank (2007), if a premature death is valued by 1 million

[**] China Labor Statistical Yearbook 2013
[††] Statistical Yearbook of the Chinese Investment in Fixed Assets 2013.
[‡‡] China Energy Statistical Yearbook 2013.
[§§] China Industry Statistical Yearbook 2011, 2013.

Yuan using value of a statistical life, the total health costs associated with air pollution are 3.8 percent of GDP, providing a proxy for the monetary benefits of avoiding mortality risk.

2.5 Scenario setup

The environmental tax rate of air pollution ranges from 1.2 Yuan/ kg-equivalent to 12 Yuan/ kg-equivalent. In addition, the tax rates reported in Table S2 vary from province to province. We set up a series of environmental policy scenarios to evaluate the effects of different environmental taxation policies on emission reduction and trade-offs between economic costs and environmental benefits (see Table 1).

Table 1 Scenario setup. One tax rate is raised individually at first (raising SO_2 tax rate, NO_x tax rate, or soot & dust tax rate) by 10 percent every time of the current tax rates (baseline scenario) to the upper bounds (12 Yuan/ kg-equivalent), and then three tax rates are raised simultaneously. Current values of the environmental tax rates of different pollutants are the average levels calculated in Table S2.

No.	Scenario	Environmental tax rates (Yuan/ kg-equivalent)					
		Pollutant	Current value (baseline)	10% increase	20% increase	. . .	The maximum value (upper bound=12.00)
Individual increase							
1	SO_2 tax	SO_2	2.90	3.19	3.48	. . .	11.89
		NO_x	3.00	3.00	3.00	. . .	3.00
		soot & dust	2.50	2.50	2.50	. . .	2.50
2	NO_x tax	SO_2	2.90	2.90	2.90	. . .	2.90
		NO_x	3.00	3.30	3.60	. . .	12.00
		soot & dust	2.50	2.50	2.50	. . .	2.50
3	Soot & dust tax	SO_2	2.90	2.90	2.90	. . .	2.90
		NO_x	3.00	3.00	3.00	. . .	3.00
		soot & dust	2.50	2.75	3.00	. . .	12.00
Simultaneous increase							
4	Three taxes	SO_2	2.90	3.19	3.48	. . .	11.89
		NO_x	3.00	3.30	3.60	. . .	12.00
		soot & dust	2.50	2.75	3.00	. . .	12.00

3. Results

3.1 Current environmental efficiency in China

In model (11), ω and δ describe the distance from the observed value to the frontier, which represents the environmental inefficiency score. In the baseline scenario, the environmental inefficiency score is 0.012, indicating that the improved potential of the economy related to environment is 1.2% in 2012. It can be interpreted as the deviation of China's actual economic and environmental performance from its frontier and level of underutilization of its resources. The distance between the actual performance and the frontier is not high to some extent, because the constraints in model (8) are strict. Goods of each industrial sector need to satisfy their own final demand, emission abatement of each abatement sector need to satisfy their own abatement target, and each primary input need to satisfy their own total social available quantity. Additionally, on the premise of maintaining the current production structure and achieving the emission reduction targets, GDP could increase by 1.64% under the environmental efficient frontier (see Table S4). Meanwhile, emissions would increase by round 1.5% because the increased level of production, which would usually be accompanied by an increase in emissions. Moreover, the abatement costs would also increase by around 0.9% due to the constraints of emission targets.

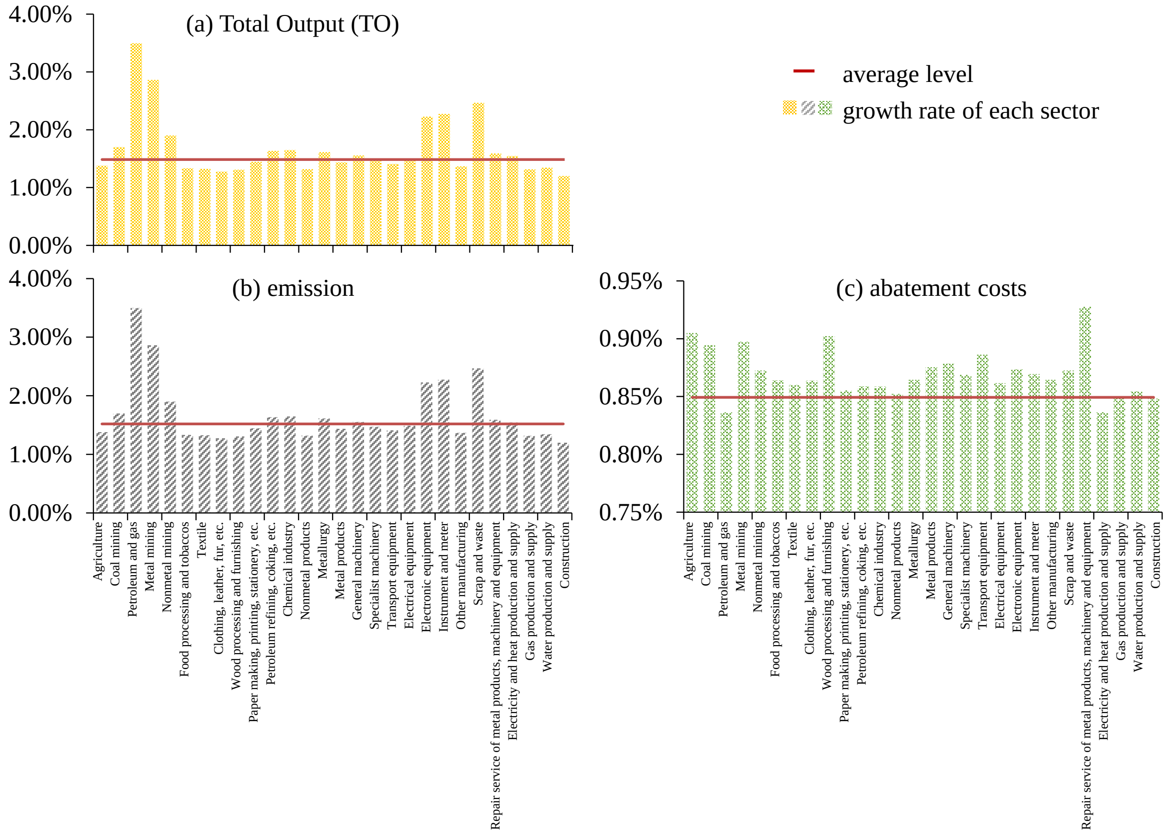

Figure 2 Improved potentials of (a) total output, (b) emission, and (c) abatement costs in different sectors. The efforts of each primary sector and secondary sector to reach the environmental efficient frontier are indicated. The horizontal axis shows sectors, while the vertical axis shows improved potentials between optimal values and observed values. Considering that emissions produced in primary sectors and secondary sectors dominate total emissions, and abatement facilities are equipped in these two kinds of sectors, the improved potentials in service sectors are miniscule. Thus, only 28 sectors (1 primary sector and 27 secondary sectors) are contained.

Constraints in model (8) act on each economic sector and each abatement sector, if production and abatement are efficient then output of any economic sector cannot be increased and any primary input cannot be decreased under the current level of emission abatement. From Figure 2 we can see that (1) improved potentials of different sectors in total output coincide with emission, indicating the high correlation between production and emission. (2) Sectors with the high level of improved potential in emission are not in keeping with abatement costs. Petroleum and gas, Metal mining, and Scrap and waste are the top three sectors of improved potential in emission, while Repair service of metal products, machinery and equipment, Agriculture, and Wood processing and furnishing rank the first three of improved potential in abatement costs.

3.2 Emission reduction effects and trade-offs between economic costs and environmental benefits

Based on the series of scenarios in Section 2.5, we evaluate emission reduction effects and trade-offs between economic costs and environmental benefits. Emission reduction effects are defined as the reduced optimal emission of the corresponding tax rate under a specific scenario compared with the optimal emission under the baseline scenario. Moreover, environmental benefit (or economic cost) is measured by the increased (or reduced) optimal abatement benefit (or GDP) of the corresponding tax rate under a specific scenario compared with the optimal abatement benefit (or GDP) under baseline scenario. Additionally, in order to synthetically measure the positive impacts on environmental benefits and the negative impacts on economic costs of the environmental taxation policy, we establish an indicator called 'abatement welfare', which is defined as the environmental benefit per unit of economic cost. Specifically, increasing abatement welfare represents the improvement in environmental benefit or the reduction in economic cost.

We compute the changes in total emissions in four scenarios with the first three scenarios of increasing specific tax rates of SO_2, NO_x, and soot & dust separately and the fourth scenario of increasing all three tax rates simultaneously. The results are presented in Table S5 and are further compared in Figures 3 and 4.

First, raising a specific tax rate, will not only lead to a decrease of emissions, but other emissions would decline as well (see Figure (3)). For instance, raising the SO_2 tax rate to the upper bound, SO_2, NO_x, and soot & dust emissions would be reduced by 11.60, 10.07, and 2.72 million kg-equivalent, respectively.

Second, the emission reduction effects of the scenario of raising three tax rates simultaneously is most significant (see Figure 4 (a)). Raising a specific tax rate of SO_2, NO_x and soot & dust to the upper bound, would lead to a reduction of total emissions by 24.40, 22.33 and 5.17 million kg-equivalent, respectively. In addition, raising three tax rates to the upper bounds, the total emissions will decrease by 52.29 million kg-equivalent, which is more than 2 times as much as the maximum total emission reduction of raising one specific tax rate scenario (24.40 million kg-equivalent in the SO_2 tax scenario). Third, the abatement welfare of the Soot & dust scenario is greater than those of other scenarios. Figure 4 (b) exhibits the changing trends of abatement welfare under the four scenarios. Although raising three tax rates simultaneously would reduce most emissions, the economic cost would be highest as well. Figure S1 illustrates changing trend of environmental benefits and economic costs with environmental tax rates in four explicit scenarios. Raising any tax rate would increase environmental benefits and economic costs. From the view of trade-offs between environmental benefits and economic costs, raising soot & dust tax rate individually would have the highest abatement benefit.

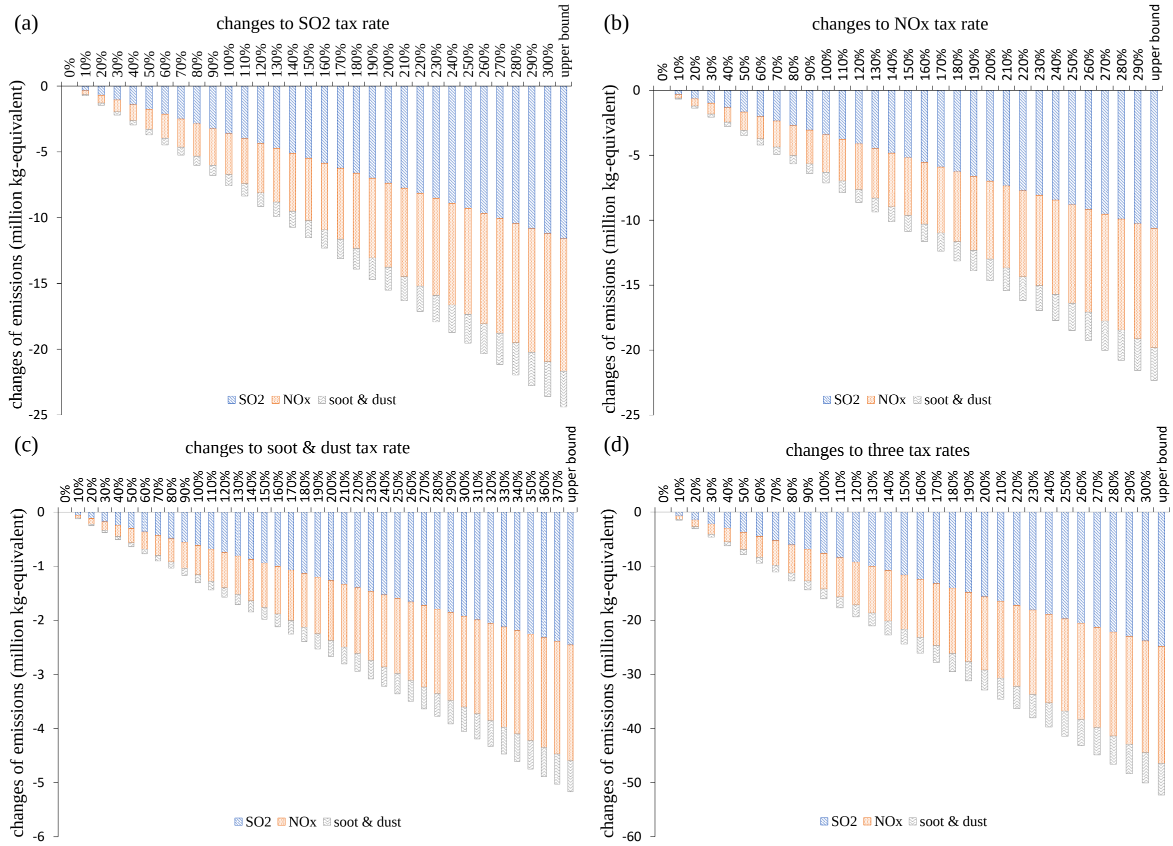

Figure 3 Changes in emissions in the four explicit scenarios. It displays the reduced emission structures of the three pollutants under the four scenarios, which are (a) raising SO_2 tax rate individually, (b) raising NO_x tax rate individually, (c) raising soot & dust tax rate individually, and (d) raising three tax rates simultaneously. Raising a specific tax rate, will not only lead to a decrease of emissions, but other emissions would decline as well.

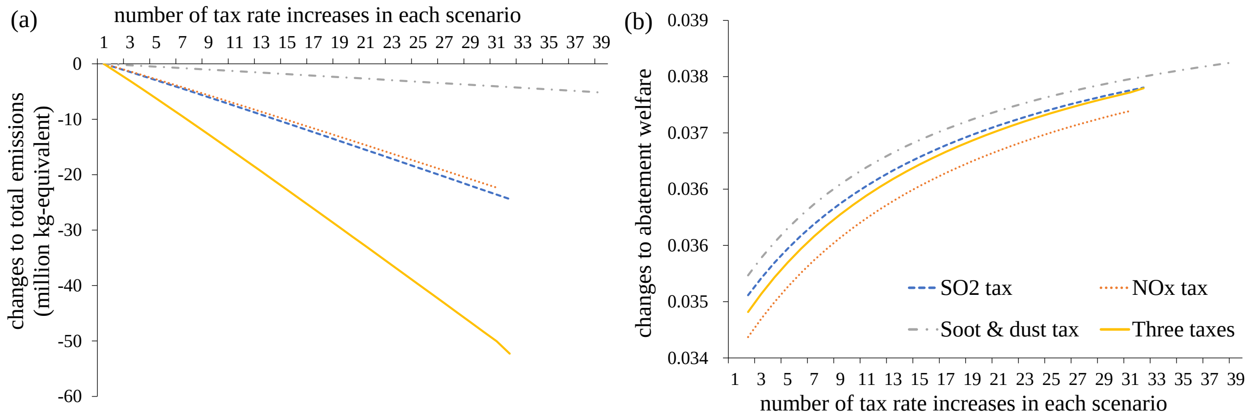

Figure 4 Changes to (a) total emissions, and (b) abatement welfare in four scenarios. Dotted lines stand for the first three scenarios, while full lines stand for the fourth scenario. Raising three tax rates simultaneously would reduce most emissions, while raising soot & dust tax rate individually would have the highest abatement benefit.

3.3 Environmental and economic impacts of different values of health costs

Higher health costs of emissions would lead to higher costs of abatement and decrease of industrial output. In this regard, we use three estimates of health costs based on different methods to figure out the uncertainty of different values of health costs on levels of production and abatement. More specifically, we use 1.2% as a lower bound (result of the adjusted human capital measurement; World Bank, 2007), 5.8% as an upper bound (total health costs and non-health costs associated with air and water pollution; Du, 2007), and 3.8% as a result of the value of statistical life measurement (World Bank, 2007).

Table 2 Impacts of different values of health costs on economy and environment. Using higher estimates for health costs would benefit both the environment and the economy.

Variable	Unit	Health costs 1.2% of GDP	3.8% of GDP	5.8% of GDP
Environmental inefficiency score	-	0.0125	0.0119	0.0115
Total emissions	Billion kg-equivalent	41.344	41.314	41.291
GDP	Billion Yuan	54,530	54,558	54,581
Changes in total emissions	%	0.073	0	-0.056
Changes in GDP	%	-0.051	0	0.042

The results of the sensitivity analyses for health costs are presented in Table 2. The second row shows the environmental inefficiency scores of the observation, lower bound and upper bound, respectively, which are the objective function values of model (11). The third and fourth rows show total emissions and GDP under the three values of health costs, while the last two rows show the percentage changes in total emissions and GDP, respectively. When the health costs increase from 1.2% to 3.8% and 5.8%, the environmental inefficiency score decreases from 0.0125 to 0.0119 and 0.0115, indicating higher environmental efficiency. Total emissions decrease from 41.344 billion kg-equivalent to 41.314 billion kg-equivalent and 41.291 billion kg-equivalent, while GDP increases from 54,530 billion Yuan to 54,558 billion Yuan and 54,581 billion Yuan, demonstrating that using higher estimates for health costs would benefit both the environment and the economy. In brief, the effects of the measurement with high health costs on both the environment and economy are positive. However, we must recognize that the identified changes are tiny, as shown in the last two rows. Even when applying the measurement of higher health costs, the reduction in total emissions and the improvement in GDP are small.

4. Conclusion and discussion

In order to compare different policy scenarios under the same efficiency benchmark, we proposed an innovative environmentally extended IO optimization model to calculate environmental efficiency.

For the purpose of identifying the wide range of economic transactions among economic and abatement sectors of an economy, we established an environmentally extended IO table by adding three abatement sectors which distinguish inputs and outputs of abatement sectors. The framework is applied to evaluate the trade-offs between environmental benefits and economic costs of environmental taxation in China. The newly proposed combined method ensures that policy scenarios could be assessed under the same technical efficiency benchmark through frontier analysis and under the input-output relations among sectors of an economy through input-output analysis. Our findings provide policy makers with a better understanding of the relationship between environment and economy and can help to create a more suitable environmental tax rate policy from the perspective of cost-benefit analysis.

The following policy implications can be drawn from the above results: (1) from a long-term perspective, increasing environmental tax rates associated with air pollution is suggested in order to reduce emissions and avoid health costs. Raising tax rates of SO_2, NO_x and soot & dust simultaneously would have the highest emission reduction effects and the lowest air pollution, with the SO_2 tax rate making the greatest contribution to emission reduction. (2) From a short-term perspective, instead of simultaneously increasing the environmental tax rates of all pollutions, increasing the environmental tax rate of each pollution step by step is advised, so as to eliminate potential negative impacts on the economy. Specifically, raising the soot & dust tax rate is suggested because it is the most cost-effective strategy (i.e., highest environmental benefit per unit of economic cost) than the other three tax rate strategies (raising the SO_2 tax rate individually, raising the NO_x tax rate individually, and raising the three pollutant tax rates simultaneously). (3) The effects of different estimates for health costs were found to be not significant, indicating different measures of health costs have little influence on the effect of environmental policy.

Although some instructive suggestions have been provided, there are some prerequisites that the policy implications would be acceptable to the government. First, in view of the industrial- or corporate-level barriers to implementing environmental taxation, it is necessary to investigate the implementation costs of enterprises in advance. Second, given the huge regional heterogeneity in China, it is better to adjust environmental tax rates to local conditions. Third, environmental protection mechanisms are based on different instruments such as governmental regulations and market-based incentives. The collaborative integration of environmental taxation policy with other energy conservation and emission reduction initiatives, for instance the establishment of carbon markets, should be accelerated. Considering technical advances, simulation of policy effects using more recent IO tables would be more practical and more flexible. Meanwhile, time series IO table enables the analysis of productivity progress and the identification of driven factor. Furthermore, spatial heterogeneity is an important issue in policy simulation, especially in China. Regional differences in terms of abatement costs and environmental benefits draw increasing attention. Further study could discuss the distribution and fairness of costs and benefits for different regions as well as the productivity progress by using more recent and time series multi-regional IO table if emissions and abatement costs become available at the subnational level.

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