Spatial heterogeneity and driving forces of environmental productivity growth in China: Would it help to switch pollutant discharge fees to environmental taxes?

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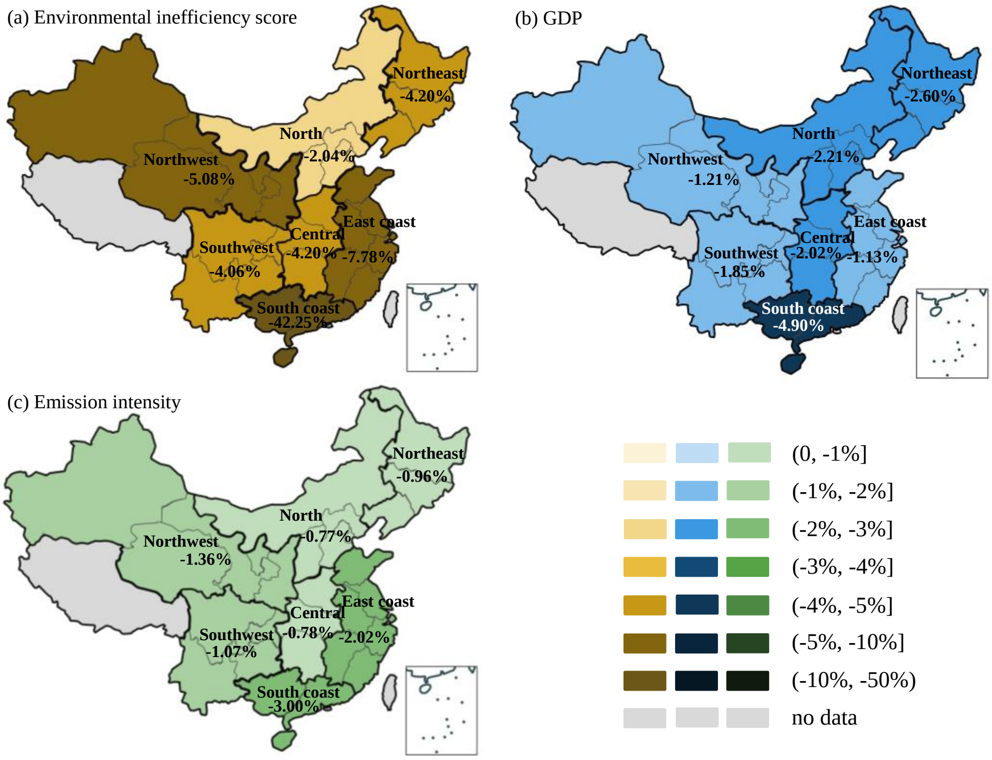
Graphical Abstract:



Note: The percentage changes of (a) environmental inefficiency score, (b) GDP, and (c) emission intensity of seven Chinese regions when changing emission charge policy from pollutant discharge fees to environmental taxes.

Abstract: Emission charge policy has recently switched from pollutant discharge fees to environmental taxes in China. Considering spatial heterogeneity, the effects of changes in emission charge policy may subject to different Chinese regions. In this study, environmental

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efficiencies of Chinese regions are evaluated through provincial environmentally extended input-output tables and a frontier-based optimization model. Driving factors of environmental productivity growth are identified through global Luenberger productivity decomposition approach. Moreover, spatial heterogeneity on the effects of change in emission charge policy on environment and economy are assessed. Results show that all regions experienced environmental productivity growth. Technology progress is the major driving factor in most regions with an average contribution of 90%, while technical efficiency regress slows environmental productivity growth in Southwest region. Switching from pollutant discharge fees to environmental taxes would decreases emission intensities by 1.42% on average, but it would have different negative impact on economic growth (-1.13%~-4.90% of regional GDP) due to spatially heterogeneous trade-offs between environmental protection and economic development. Addressing such spatial heterogeneity provide not only a basis for diversified tax rate determination but also a framework for other environmental policy assessment.

Keywords: environmental efficiency; emission charge policy; productivity decomposition; IOA; DEA

1. Introduction

Industrialization and urbanization caused by rapid economic development lead to over-energy consumption in China. Currently, China is the biggest country of energy consumption in the world, ranking the top of the growth in global energy consumption for 17 years (BP, 2018). In 2017, China accounted for 23.2% and 33.6% in the global energy consumption and the growth in global energy consumption, respectively (BP, 2018). Due to the excessive energy consumption, environmental pollutions are becoming increasingly serious in China, especially air pollutions and water pollutions. During the 12th Five-Year period, China dominated approximately 30% of global sulfur dioxide (SO_2) emission and 20% of global nitrogen oxides (NO_x) emission per annum (Zhang et al., 2018). Meanwhile, particulates emissions, including soot and dust (SD) (Liang et al., 2016) and particulate matter (Song et al., 2017) are also at high levels in China. Because of the severe air pollutions, the number of heavy pollution days raise continually and about one third of Chinese cities struggle with fog and haze issues (Xie et al., 2018). Beside air pollutions, series of water pollutions intensify the problem of scarcity of drinking water supply. For instance, the Yangtze River, which is the source of drinking water for up to 800 million (M) people, undertakes the most proportion of national water polluted industrial activities (Chen et al., 2018b). As a result of water pollution, there are about 190M people fall sick and 60 thousand people die each year in China (Tao & Xin, 2014). Moreover, heavy metal pollutions like Hg, Cd, Pb, As, Cu, and Zn are other factors of public health risk (Li et al., 2014).

Facing severe environmental and ecological problems and their effects on public health, Chinese government has enacted laws and implemented policies to handle environmental problems since the last century (Feng & Liao, 2016). For example, in order to control emissions, Air Pollution Prevention and Control Action Plan has been issued in 2013 and Environmental Protection Law has been implemented in 2015 in China, which have pressured local authorities to increase penalties for environmental violations. Additionally, Chinese government has set explicit emission reduction targets for major pollutions since the 11th Five-Year Plan (Yang et al., 2018). And ecological protection targets are completed in the 13th Five-Year Plan for Eco-environmental Protection. Those policies did have positive effects on slowing down the rate of emission growth to some extent. In 2017, carbon emission increased 1.6% in China, which was the half of the average rate over the past decade (BP, 2018). Other pollutions met the corresponding emission targets as well (Wang et al., 2014). However, environmental policies associated with emission abatement and environmental protection will limit production and further reduce economic growth, in other words, there are trade-offs between environmental protection and economic development. It has been confirmed that strict environmental policies would have a negative impact on GDP in China (Ahmed & Ahmed, 2018).

Therefore, both economic and environmental perspectives need to be contained in order to have a more comprehensive estimation of policy effects. Environmental efficiency is one of the solutions to measure policy effects on economy and environment. In this study, environmental efficiency is defined as the improved potential to achieve more industrial outputs with less resource inputs as well as more emission abatement. Methods of efficiency estimation can be roughly divided into statistical approaches (Semenyutina et al., 2014), parametric analysis, e.g. linear programming (Du & Mao, 2015), parametric meta-frontier analysis (Du et al., 2016), and parametric hyperbolic distance function approach (Duman & Kasman, 2018), and non-parametric analysis. Data envelopment analysis (DEA) is a widely used non-parametric approach to measure sector-varying (Bi et al., 2014), region-varying (Chen & Jia, 2017), or time-varying (Wang et al., 2013) environmental efficiency. Furthermore, DEA can also be improved by combing life cycle assessment (Lorenzo-Toja et al., 2018), input-output analysis (IOA) (Xing et al., 2018), and index or statistical analysis (e.g. Malmquist index used in Woo et al. (2015); bootstrapping approach applied in Yang & Zhang (2018)). However, studies mentioned above have certain limitations. First, the results were probably biased because environmental efficiencies were measured under the independent constraints of economy and environment. Second, the sensitivity to environmental policy depends on different industrial sectors, high energy intensity sectors and high emission sectors tend to be strongly influenced by environmental policies. But the difference among industrial sectors and the material flow existed in industrial sectors are neglect. Third, there is obvious heterogeneity among different regions in China, environmental efficiency measured at national level cannot figure out the regional diversity.

In this study, in order to measure environmental efficiency in view of the inter-sector heterogeneity and material flow existed in industrial sectors, we combine IOA and DEA and propose a frontier-based optimization model with uniform formulations of both economic and environmental constraints. For purpose of evaluating effects of emission charge policies on environment and economy, we estimate environmental efficiencies in seven geographical regions in China (the region category is attached in Table S1) using this optimization model. First, we calculate the environmental inefficiency scores of seven Chinese regions through the conventional model and the improved optimization model. Then, in order to evaluate the environmental productivity change of each region, we decompose the driving factors of environmental inefficiency score measured by DEA into technical efficiency change (EC) and best practice gap change (BPC) by using global Luenberger productivity indicator (GLPI). Finally, we compare the changes of environmental efficiency, GDP and the emission intensity under different emission charge policies and evaluate the synergistic effects of pollutant emission and carbon emission reduction.

This study contributes to the existing research at the theoretical and the application level in the following aspects. First, taking spatial heterogeneity and the trade-offs between economic development and environmental protection into consideration, the effects of switching pollutant discharge fees for environmental taxes are assessed. Second, the compiled environmentally extended input-output tables for 30 Chinses provinces distinguish abatement costs and environmental benefits from monetarily valued material flows among various industrial sectors. Third, the frontier-based optimization model provides a framework of environmental efficiency measurement which has the uniform and connective constraints of economy and environment. Based on this model, an environmental efficient benchmark could be obtained, so that different policy scenarios could be compared without the impacts of efficiency change. Fourth, environmental productivity growth and its driving factors are identified based on Luenberger productivity indicator.

2. Methods and data

2.1. Environmentally extended input-output analysis for efficiency measurement

Environmentally extended input-output analysis (EEIOA) is widely applied to assess the environmental impacts related to energy consumption (Chen et al., 2018a), pollutant emission, e.g. CO2 (Meng et al., 2018) and mercury emissions (Li et al., 2015), efficiency measurement (Aguilar-Hernandez et al., 2018), and improved potential evaluation at regional level (Mi et al., 2015) or national level (Mi et al., 2017). The advantage of EEIOA is that the relationship between environment and economy is treated in one unitary and closed monetarily valued material flow. Besides, each sector's characteristics can be captured through multi-sector input-output table. In addition, impacts of environmental policies include both the effects of policy itself and the effects of efficiency changes associated with policy reform. Thus, in order to evaluate the effects of environmental policy itself on environment and economy, the impacts of efficiency change required to be eliminated, so that different policy scenarios could be compared under the same environmental efficient benchmark. Therefore, frontier-based optimization model is developed by combing EEIOA and DEA to calculate environmental inefficiency score. The framework is illustrated as in Figure 1.

Aims	Methods	Policies	Years
Environmental efficiency calibration	Conventional model + Frontier-based optimization model	Environmental taxes	2012
Environmental productivity decomposition	Frontier-based optimization model + Luenberger productivity indicator	Environmental taxes	2012 + 2007
Environmental policy simulation	Frontier-based optimization model	Environmental taxes + Pollutant discharge fees	2012

Figure 1. The research framework. Conventional model and Frontier-based optimization model is represented as model (1) and model (2), respectively.

Taking the reference of Mahlberg & Luptacik (2014), the conventional model (model (1)) is proposed with the separate emission constraint and economic constraint based on the conventional input-output table. δ is environmental inefficiency score, indicating the improved potential away from the frontier of the specific year to be analyzed. x is the n×1 total output vector, while e is the m×1 total produced pollution vector. A is the n×n intermediate use coefficient matrix, indicating the intermediate use per unit of total output of each industrial sector. EI is the m×n emission intensity matrix, showing the emission per unit of total output of each industrial sector. While B is the k×n primary input coefficient matrix, representing the primary input per unit of total output of each industrial sector. n, m, and k stand for the number of industrial sector, the kind of emission, and the number of primary input, respectively. In this study, n, m, and k equals to 42, 16, and 4, respectively. Notations with superscript 0 are parameters. IM^0, IF^0, ERR^0, and TFU^0 come from the conventional input-output table, meaning imports vector, inflow vector, error vector and total final use vector of industrial sector, respectively. AT^0 is the m×1 emission abatement target, while z^0 is the k×1 social available vector. This model aims at optimizing the environmental inefficiency score. The first constraint means that for each industrial sector, the optimal total output minus intermediate use should not be less than the observed total final use. The second constraint means that for each pollutant, the optimal produced pollution minus emission load should not be less than the observed abatement target. While the third constraint means that for each primary input, the optimal primary input should not be higher than the observed social available resource. In this model, all economic variables and parameters are valued in monetary unit Yuan, while all environmental variables and parameters are valued in physical unit kg-equivalent.

$$\begin{aligned}
&\max_{x,e,\delta}\ \delta \\
&s.t. \\
&x - A\cdot x + IM^0 + IF^0 - ERR^0 \geq (1+\delta)TFU^0 \\
&e - EI\cdot x \geq (1+\delta)AT^0 \\
&B\cdot x \leq (1-\delta)z^0 \\
&x,\ e,\ \delta \geq 0
\end{aligned} \tag{1}$$

As mentioned before, the conventional input-output table cannot figure out emission abatement cost and abatement benefit. Besides, inputs for productive activities and inputs for abatement activities cannot be identified as well. That is to say, the environmental value is aggregated with productive value in the conventional input-output table.

In order to distinguish inputs for emission abatement and quantify environmental value, we establish environmentally extended input-output tables (Wang et al., 2018) for each Chinese province in 2007 and 2012 by introducing sixteen emission abatement sectors (see Table S2). Intermediate inputs from industrial sectors to emission abatement sectors are served by emission abatement costs, while intermediate inputs from emission abatement sectors to industrial sectors are presented by emission charges, which can be understood as emission rights. Regarding final outputs of emission abatement sectors, environmental benefits associated with emission abatement denote the total final use of emission abatement sectors. Additionally, total outputs and primary inputs of emission abatement sectors are calculated through the balance of Leontief input-output matrix. Thus, monetary values of environment and economy can be provided through an integrated and balanced input-output matrix.

Based on these environmentally extended input-output tables, an improved environmental efficiency measured model is proposed as model (2). Compared with the conventional model, the improved one has two significant superiorities. First, it is capable of capturing the interrelated relationship between environment and economy under one integrated framework. Any changes in emission control and emission discharge affected by environmental policy will have an effect on material flow among industrial sectors, and this effect can be measured in the extended input-output table and the improved model. Second, the improved model distinguishes inputs for emission abatement and separates environmental values (such as emission abatement cost and emission charge) from productive values. Moreover, all variables and parameters in model (2) are valued in monetary unit Yuan.

$$
\begin{aligned}
&\max_{x_{1,t},x_{2,t},\delta_t} \ \delta_t \\
&s.t. \\
&x_{1,t} - A_{11,t}\cdot x_{1,t} - A_{12,t}\cdot x_{2,t} + IM_t^0 + IF_t^0 - ERR_t^0 \geq (1+\delta_t)TFU_{1,t}^0 \\
&x_{2,t} - A_{21,t}\cdot x_{1,t} - A_{22,t}\cdot x_{2,t} \geq (1+\delta_t)TFU_{2,t}^0 \\
&B_{1,t}\cdot x_{1,t} + B_{2,t}\cdot x_{2,t} \leq (1-\delta_t)z_t^0 \\
&x_{1,t},\ x_{2,t},\ \delta_t \geq 0
\end{aligned}
\tag{2}
$$

Here, all notations are derived from the environmentally extended input-output table. The subscript t is a symbol of the accounting periods, which will be detailed explained in Section 2.2. δ_t, IM_t^0, IF_t^0, ERR_t^0, z_t^0 have the same meanings as in model (1). x_1 and x_2 serves as n×1 total output vector of industrial sector and m×1 total output vector of emission abatement sector (environmental value), respectively. Similarly, TFU_1 and TFU_2 represents total final use of industrial sector and total final use of emission abatement sector (environmental benefit associated with emission abatement), respectively. B_1 and B_2 show primary input coefficient matrixes of industrial sector (k×n) and emission abatement sector (k×m). A_{11} is the n×n intermediate input coefficient matrix from industrial sector to industrial sector, which has the same meaning but different value with A in model (1) because of the environmental extension. A_{12} is the n×m intermediate input coefficient matrix from industrial sector to emission abatement sector, representing emission abatement cost per unit of environmental value. A_{21} is the m×n intermediate input coefficient matrix from emission abatement sector to industrial sector, denoting emission charge per unit of total industrial output. A_{22} is the m×m intermediate input coefficient matrix from emission abatement sector to emission abatement sector, which is a zero valued matrix because environmental taxes are levied at economic sectors and abatement costs (or environmental taxes) related to secondary emission during abatement process are included in economic sectors. The formulation of model (2) is similar with model (1), except the second constraint. Since all environmental concepts are quantified monetarily in the improved input-output table, the second constraint gives the lower bound of abatement benefit instead of the physical valued emission abatement target of each emission abatement sector, denoting the optimal environmental value minus emission charge should not be less than the observed abatement benefit.

2.2. Luenberger productivity indicator for driving factors decomposition

Changes of environmental inefficiency score between different years indicates the improvement or deterioration of environmental productivity. One of the aims of this study is to evaluate the environmental productivity change of each region over two separate years, which are 2007 and 2012. For this purpose, taking the reference of Wang et al. (2016), we define the global Luenberger productivity indicator (GLPI) over the two years to measure the change of environmental productivity. GLPI is superior to the traditional Luenberger productivity indicator in solving several problems such as failing circularity, spurious technical regress and infeasible situation (Wang & Wei, 2016). Equation is shown as follows:

$$GLPI(x_{1,t},x_{2,t};x_{1,t+1},x_{2,t+1})=\delta_t^G(x_{1,t},x_{2,t})-\delta_{t+1}^G(x_{1,t+1},x_{2,t+1}) \qquad (3)$$

The progress of environmental productivity could be explained as the reduction of environmental inefficiency score. Thus, the difference of global environmental inefficiency scores between the two years is used to measure the environmental productivity change. The positive, negative, and zero values mean improvement, deterioration, and invariability of environmental productivity, respectively. δ^G is the global environmental inefficiency score and can be calculated by model (4), indicating the improved potential away from the frontier of the panel data set for a period. $\delta_t^G(x_{1,t},x_{2,t})$ and $\delta_{t+1}^G(x_{1,t+1},x_{2,t+1})$ are distinguished by the two separate periods t and t+1. In this study, t and t+1 represent 2007 and 2012, respectively.

$$
\begin{aligned}
&\max_{x_{1,t},x_{2,t},\delta_t^G} \ \delta_t^G \\
&s.t. \\
&x_{1,t} - A_{11,t}\cdot x_{1,t} - A_{12,t}\cdot x_{2,t} + IM_t^0 + IF_t^0 - ERR_t^0 \ge (1+\delta_t)TFU_{1,t}^0 \\
&x_{2,t} - A_{21,t}\cdot x_{1,t} - A_{22,t}\cdot x_{2,t} \ge (1+\delta_t)TFU_{2,t}^0 \\
&B_{1,t}\cdot x_{1,t} + B_{2,t}\cdot x_{2,t} \le (1-\delta_t)z_T^0 \\
&x_{1,t},\ x_{2,t},\ \delta_t^G \ge 0
\end{aligned}
\tag{4}
$$

Model (4) is the optimization model for global environmental inefficiency score. The subscript t is a symbol of the exact year to be analyzed. All constrains are same as those in model (2) except the definition of z_T^0. In model (2), z^0 is the social available vector of a specific year. While in model (4), z_T^0 is the maximum value of social available vector during a period (between t and t+1 in this study), providing the global input frontier. Solving model (4) twice for year t and t+1, the two years' global environmental inefficiency scores can be obtained.

Furthermore, in order to figure out the main driving factors of the environmental productivity change in each region, GLPI is decomposed into efficiency change (EC) and best practice gap change (BPC), which are illustrated in Eqs. (5) and (6). EC is the difference of the two separate periods of environmental inefficiency scores (δ_t). While BPC is the difference of the two separate periods of the distance between global environmental inefficiency scores (δ_t^G) and environmental inefficiency scores (δ_t).

$$EC = \delta_t(x_{1,t}, x_{2,t}) - \delta_{t+1}(x_{1,t+1}, x_{2,t+1}) \tag{5}$$

$$BPC = [\delta_t^G(x_{1,t}, x_{2,t}) - \delta_t(x_{1,t}, x_{2,t})] - [\delta_{t+1}^G(x_{1,t+1}, x_{2,t+1}) - \delta_{t+1}(x_{1,t+1}, x_{2,t+1})] \tag{6}$$

EC is the average gain or loss related to the technical efficiency change from period t to period t+1, capturing the movement with the same or opposite direction of the technology frontier. BPC is the average gain or loss due to the technology change from period t to period t+1, indicating the best practice gap change between the global technology frontier and each period's technology frontier (Wang et al., 2016). The positive (or negative) values of EC and BPC represent technical efficiency increase (or decrease) and technology progress (or regress), respectively.

2.3. Data sources

Chinese provincial input-output tables are issued every five years by Department of National Economic Accounting, National Bureau of Statistics of China. The last two issues of provincial input-output tables with 42 industrial sectors of 30 Chinese provinces in 2007 and 2012 are used as the basic economic datasets. The sector category is in line with that in 2012 input-output tables (see Table S2). Given that labour and capital are the main sources of extensible primary inputs, the social available resource z^0 is calculated based on the weighted average of the extensible rates of labour and capital with the weight equaling to the proportion of each primary input to the total primary input. The extensible rates for the whole country and 30 regions are measured based on unemployed population and depreciation of original value of fixed assets, approximately ranging from 10% to 50%. For easier discussion, we assume the same extensible rate in all primary inputs and all provinces, thus we take 30% as the extensible rate of primary input and 130% as the social available resource z^0.

As for environmental data, we get the national emission loads of the sixteen pollutants in 2007 and 2012 from Chinese Environmentally Extended Input-Output (CEEIO) Database (Liang et al., 2017). Values of national emission abatement cost come from Department of Industry Statistics of National Bureau of Statistics of China and are distributed to each pollutant by their emission proportion. We allot the national emission loads and national emission abatement cost to provincial ones by the provincial energy consumption proportion. Total final use of emission abatement sector (environmental benefit associated with emission abatement) is measured by the product of emission abatement load and the health costs per unit of emission. According to World Bank (2007), total health costs of air pollution and water pollution in China is 3.8% of GDP and 2.0% of GDP, respectively.

2.4. Pollutant equivalents transformation

Given that each pollutant has different environmental effects, same emission loads of different pollutants will pose different degrees of negative impacts on environment. Thus, it is necessary to unify the negative effects of various pollutants on environment and public health. China's Ministry of Environmental Protection published a list of taxable pollutants and the corresponding "pollutant equivalent", which could be applied to transfer the physical units (E_{phy}) of emission loads of different pollutants to the equivalent units (E_{equ}) according to their environmental and health impacts (Zhang et al. 2018). The equivalent units (k) are listed in Table S3, serving as the coefficients to divide emission loads in physical units (E_{phy}): $E_{equ}=E_{phy}/k$.

3. Results

3.1. Environmental efficiency calibration

Figure 2 shows the bias degrees of improved potential at regional level. Improved potential implies the distance between optimized value and observed value. The conventional model tends to underestimate environmental inefficiency score, economic indicators (GDP and total output), and environmental indicators (emission and emission intensity). The bias degree of environmental inefficiency score is not obvious. Specifically, the biased degree of environmental inefficiency score in South coast region rank the top, valued -21%. While the biased degree of emission intensity is large, which is -48% in Northeast region, -4% in North region, 362% in East coast region, -85% in South coast region, -64% in Central region, -35% in Northwest region, and -333% in Southwest region, respectively. It can be explained that values of emission intensity are too tiny, any small changes would result in large bias degrees. From the spatial heterogeneity perspective, the conventional model is inclined to underestimate indicators of most regions, but overestimate indicators of economically developed region. Specifically, bias degree in East coast region of environmental inefficiency score, GDP, total output, emission, and emission intensity is 3%, 14%, 41%, 86%, and 362%, respectively. Besides, the bias degrees of five indicators in North region is the lowest. Over all, the improved model corrects the overestimated economic and environmental indicators in East coast region, and corrects the underestimated economic and environmental indicators in other regions.

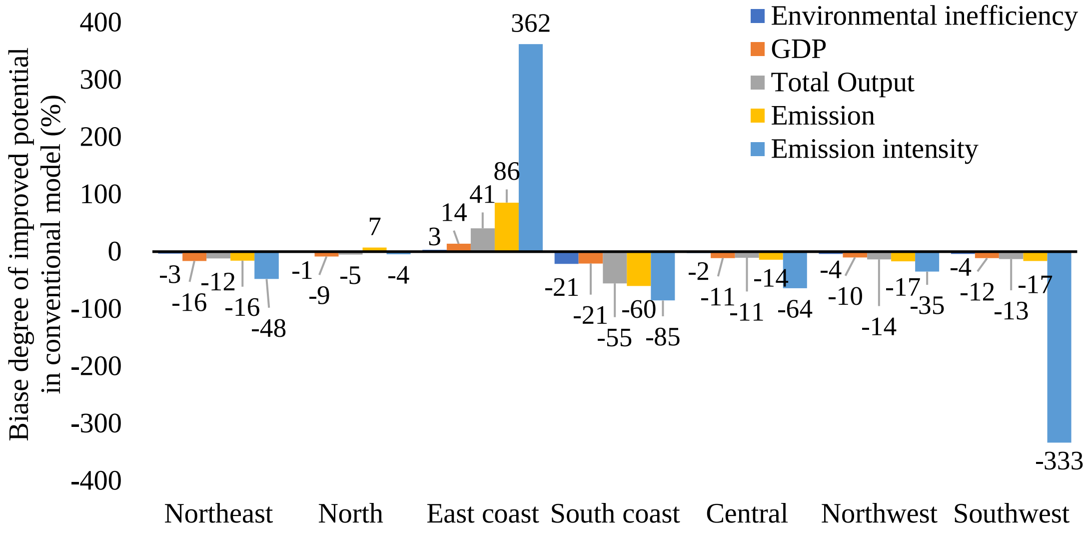

Figure 2. The bias degree of improved potential of model (1) over model (2) in seven Chinese regions. Five indicators are considered, which are environmental inefficiency, GDP, total output, emission, and emission intensity. Improved potential dominates the difference between optimal value and observed value. Values in this figure are measured through dividing the difference between the improved potentials of model (1) and model (2) by the improved potential of model (2), representing the bias degree of improved potential of model (1) compared with model (2). The positive (or negative) value means that model (1) overestimates (or underestimates) the corresponding indicator.

3.2. Environmental productivity decomposition

Figure 3 displays the environmental productivity change and the corresponding driving factors of each region. North region and Northwest region are the bottom two regions in environmental productivity progress, valued 0.0860 and 0.0994 in GLPI, respectively (see Table 1). It is because that industrial-oriented economic structures in these regions pose negative effects on environment and further on environmental efficiency. For instance, North region has intensive high energy consumption and high emission enterprises, such as thermal power plants, coking factories and large installed electricity generation facilities (Liu et al., 2018). Specially, the large vehicle population in Beijing and the high level of agricultural and animal activities in Hebei and Henan provinces aggravate emission degree in North region (Liu et al., 2018). Besides, the developed mining and oil processing industries produce serious environmental pollution due to the rich mineral resources in Northeast region.

Table 1 Environmental inefficiency score and the driving factors decomposition. Environmental inefficiency scores of the two specific periods are calculated by model (2). Environmental productivity changes from 2007 to 2012 are represented by GLPI, which is measured by model (4). Two driving factors BPC and EC are decomposed from GLPI by Eqs. (5) and (6).

Region	Environmental inefficiency score		BPC	EC	GLPI	Percentage contribution (%)	
	2007	2012				BPC	EC
Northeast	0.0924	0.0897	0.1147	0.0025	0.1172	97.87	2.13
North	0.0850	0.0783	0.0787	0.0073	0.0860	91.51	8.49
East coast	0.0691	0.0691	0.1320	0.0016	0.1336	98.83	1.17
South coast	0.0870	0.0393	0.0672	0.0478	0.1149	58.45	41.55
Central	0.0962	0.0968	0.1673	-0.0004	0.1668	100.26	-0.26
Northwest	0.0854	0.0722	0.0868	0.0126	0.0994	87.34	12.66
Southwest	0.0559	0.0957	0.2493	-0.0392	0.2101	118.64	-18.64

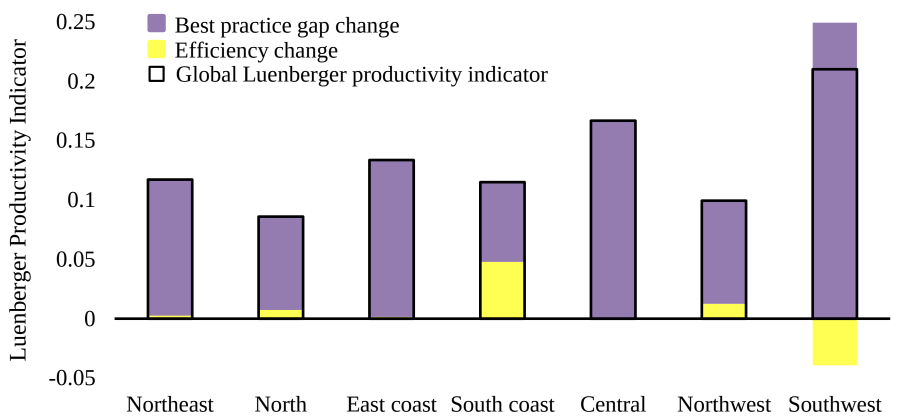

Figure 3. Environmental productivity indicators of seven Chinese regions. The bars outlined in black show GLPIs. The purple colored bars and yellow colored bars represent BPCs and ECs, respectively. GLPI is the sum of EC and BPC. The positive and negative values of GLPI stand for environmental productivity growth and reduction, respectively. The positive (or negative) values of EC and BPC represent technical efficiency increase (or decrease) and technology progress (or regress), respectively.

Furthermore, according to the positive or negative driving factors, the seven Chinese regions can be divided into three modes, which are technology dominant mode (mode one), efficiency impeditive mode (mode two), and co-driven mode (mode three). Most of the regions belong to mode one, except South coast region and Southwest region. According to GLPI, environmental productivity increases by 0.1172 in Northeast region, 0.0860 in North region, 0.1336 in East coast region, 0.1668 in Central region, and 0.0994 in Northwest region, respectively. And technical improvement dominates 97.87%, 91.51%, 98.83%, 100.26%, and 87.34%, respectively (see Table 1). Since the 1980s, in order to comply with the international development tendency and reconstruct national economic development structure as well as redevelop an environmental-friendly oriented economy, China has implemented the following development strategies successively: Coastal Development Strategy for Eastern coast region, the Great Western Development Strategy for Northeast region and Northwest region, Revitalization of the Old Northeast Industrial Base Strategy for Northeast region, and Mid-China Rising strategy for Central region. This series of strategies encourages local factories to renovate technology and eliminate backward productive technique. Thus, the best practice gap compared with regions in the frontier has been narrowed and the technology progresses a lot.

Southwest region belongs to mode two due to the negative EC (valued -0.0392). However, GLPI of Southwest region (0.2101) is the highest over the seven regions, even if the technical efficiency change has a passive effect on environmental productivity progress. The high level of environmental productivity progress in Southwest region might be correlated with the excellent resource endowment and environmental conditions. It has been pointed out that the abundant energy and forest resources and well-developed clean electricity generation method of hydropower lead to low carbon emission (Tao et al., 2016), and further lead to high environmental efficiency. However, the industrial development actions which have negative impacts on the local environment leads to a significant decline in technical efficiency. For example, the establishment of the large petrochemical industrial base has resulted in air and water pollution in Sichuan province. Moreover, pollutant emissions from local phosphorus chemical industry generates chronic poisoning to nearby residents and livestock in Yunnan province.

Mode three includes South coast region. The two driving factors have similar effects on environmental productivity change in this region. More specific, BPC and EC contribute to environmental productivity progress by 58.45% and 41.55%, respectively. On one hand, from the national trade perspective, South coast region is the outflow place of air pollution and solid waste (Wu, 2016). On the other hand, because of the superior geographical position and abundant capital, South coast region can timely learn advanced emission control technology. Thus, technical efficiency progress and technology improvement promote environmental productivity at the same time.

3.3. Effects evaluation of emission charge policies on economy and environment

In this study, two emission charge policies are considered, which are pollutant discharge fees and environmental taxes. From the beginning of 2018, environmental taxes policy has been implemented with the enaction of "Environmental Protection Tax Law", replacing the pollutant discharge fees policy which was implemented from 2003. The environmental taxes policy formulates environmental tax rate for each taxable pollution. It has been decided that the range of environmental tax rates of air pollution and water pollution is from 1.2 Yuan/ kg-equivalent to 12 Yuan/ kg-equivalent and from 1.4 Yuan/ kg-equivalent to 14 Yuan/ kg-equivalent, respectively. While the pollutant discharge fees of air pollution and water pollution is 0.6 Yuan/ kg-equivalent and 0.7 Yuan/ kg-equivalent, respectively. The detailed tax rates of different pollutions in different provinces are listed in Table S4.

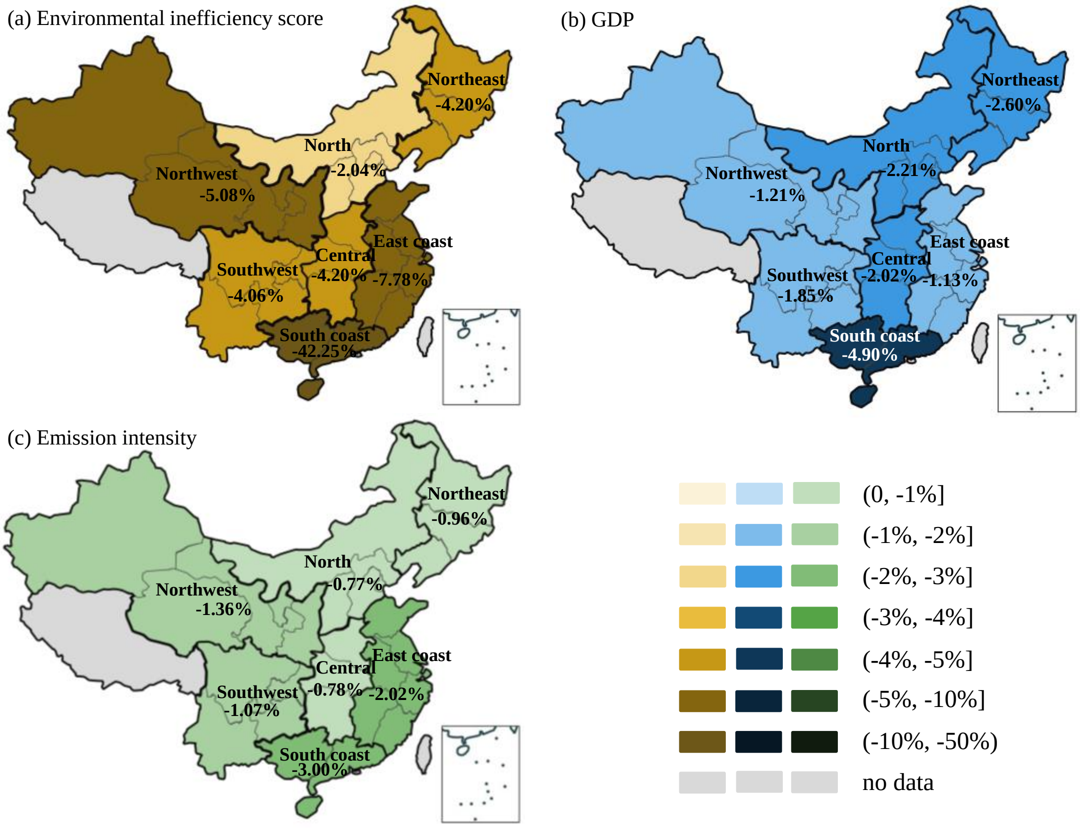

Figure 4. The percentage changes of (a) environmental inefficiency score, (b) GDP, and (c) emission intensity of seven Chinese regions when changing emission charge policy from pollutant discharge fees to environmental taxes. The black thick lines are the regional boundaries, while the grey thin lines are the provincial boundaries. Blocks in grey are not included in our study due to the lack of data, which are Tibet, Taiwan, Hongkong, and Macao, respectively. Darker colored block represents higher percentage change. The range of percentage change of each hierarchical color is shown as the legend.

In order to evaluate the effects of the increased tax rates of various pollutions on efficiency, economy, and environment, we calculate the percentage changes of environmental inefficiency scores, GDP, and emission intensity of seven Chinese regions when changing environmental policy from pollutant discharge fees to environmental taxes policy (shown as Figure 4). Percentage changes of environmental inefficiency score stand for the effect of environmental policy on environment, percentage changes of GDP reveal the effect of environmental policy on economic development, while percentage changes of emission intensity show the complex effect on both environment and economy. It can be seen that raising emission charge, environmental inefficiency scores would have obvious declines, and emission intensity would be decreased by 1.42% on average. We further calculate the median for each indicator, which is illustrated in Table 2. According to the relationship between absolute values and median of each indicator, these seven regions can be additionally divided into four patterns, which are high economic effect – high environmental effect (H-H) pattern, high economic effect – low environmental effect (H-L) pattern, low economic effect – high environmental effect (L-H) pattern, and low economic effect – low environmental effect (L-L) pattern.

Table 2 Percentage changes and medians of three indicators. Absolute values which are higher than median represent that changes in these regions are more obvious, while the opposite means that changes in those regions are less significant.

Region	Environmental inefficiency score	GDP	Emission intensity
Northeast	-4.20%	-2.60%	-0.96%
North	-2.04%	-2.21%	-0.77%
East coast	-7.78%	-1.13%	-2.02%
South coast	-42.25%	-4.90%	-3.00%
Central	-4.20%	-2.02%	-0.78%
Northwest	-5.08%	-1.21%	-1.36%
Southwest	-4.06%	-1.85%	-1.07%
Median	**-4.20%**	**-2.02%**	**-1.07%**

South coast region belongs to H-H pattern, whose percentage change of environmental inefficiency score and GDP values -42.25% and -4.90% respectively. Besides, percentage change of emission intensity is the highest, indicating raising tax rates would have the lowest emission per unit of total output in South coast region. It is because that industries in South coast region adjust their productive structures and relocate factories' sets due to the strict environmental regulation. Thus, the reduced emission affected by environmental policy poses positive effects on emission intensity. For example, in recent years, small sized enterprises are moved from Guangdong province to Hunan and Jiangxi province, which makes South coast region an outflow place of air pollution transfer (Wu, 2016). H-L pattern includes Northeast region and North region. They have high percentage changes of GDP, valued -2.60% and -2.21%, but low percentage changes of environmental indicators. Economic development structures of Northeast region and North region depend mainly on heavy industry and conventional energy structure. Industrial productive activities are relied on an over-consumption of fossil fuel combustion (Wang & Zhao, 2017). However, the increase of emission charge makes enterprises reduce production intensity to reduce emission. Therefore, the low production intensity delays the speed of economic development. While L-H pattern contains Northwest region and East coast region, which rank the last two regions in percentage change of GDP. Regarding to East coast region, it has adequate financial support and advanced productive technology. Hence, the developed emission abatement technique can satisfy the abatement target instead of reducing production intensity to avoid emission. Moreover, L-L pattern includes Central region and Southwest region. In this pattern, all indicators' percentage changes are at low levels, indicating the weak effect of environmental policies on environmental protection and economic development. On one hand, raising emission charge would reduce the local emission and increase the environmental efficiency. On the other hand, raising environmental tax rates would lead to the reconstruction of the national industrial production layout, pollution would be transferred to Central region and Southwest region due to the emission leakage effect. Thus, local emission would increase and environmental efficiency would decrease. Therefore, the percentage changes of all indicators are not obvious because the positive effects neutralize the negative effects.

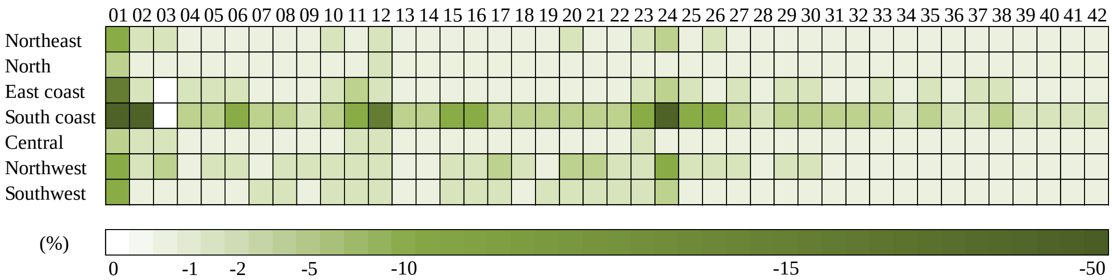

Figure 5. The synergistic effects of different emission charge policies on carbon emission reduction. The hierarchical color shows the percentage change of carbon emission associated with total output when raising emission charge from pollutant discharge fees to environmental taxes. Rows mean regions, while columns represent industrial sectors (see Table S2).

From the above results we can see that, tightening emission charge policy would reduce emission and reduce total output at the same time because of the trade-offs between environment and economy. As we know, industrial productive processes are often accompanied by various emissions, especially carbon emission. Thus, the reduction in total output due to the higher taxes of environmental pollutions would also have synergistic effects on carbon emission reduction. For purpose of discussing this effect of different sectors in different regions, we measure the percentage change of carbon emission associated with total output under pollutant discharge fees policy and environmental taxes policy (see Figure 5). In this study, we only consider the synergistic effects of carbon emission reduction due to the total output reduction, other factors such as abatement technical improvement or trade diversion are not included. Besides, we assume that carbon emission factor is fixed under different emission charge policies. As reflected from Figure 5, carbon emission in all regions decreases significantly in agriculture sector (code 01), valued -11.18% in Northeast region, -6.37% in North region, -15.96% in East coast region, -44.06% in South coast region, -9.96% in Central region, -11.72% in Northwest region, and -12.66% in Southwest region, respectively. Additionally, compared with other regions, carbon emission reduction in South coast region would be the most obvious, indicating that the emission charge policy would have more obvious effects on both environment and economy in South coast region, which, again, verifies the results in Section 4.2.

4. Policy implications

Some policy implications can be derived from the estimation of driving factors of environmental productivity: 1) for technology dominant regions, further actions should aim at increasing environmental efficiency. To do that, the local government should accelerate the transfer of industrial development structure from high energy-intensive structure to low energy-intensive structure by decreasing fossil fuels consumption and increasing clean energy consumption. 2) For efficiency impeditive regions, they should develop industries that meet local environmental requirements. More specific, reduction of iron production capacity, shutdown coal-fired power plants, and replacement industrial boilers should be considered, which are consistent with the conclusions in Qi et al. (2017) and Liu et al. (2018). 3) For co-driven regions, they should promote pollution control technologies and experiences to assist other regions with low level of environmental efficiency to progress.

Furthermore, some suggestions can be proposed from the analysis of economic and environmental impacts of emission charge policy: 1) for H-H regions, raising environmental tax rates are suggested since it could increase environmental efficiency obviously. Although GDP declines pronouncedly because of the trade-offs between environment and economy, the decrease of emission intensity indicates that environmental impact is greater than economic impact. 2) For H-L regions, environmental policies are advised to adjusted based on the local development targets. If the local strategy focuses on decreasing emission intensity and puts less emphasis on increasing GDP, then raising environmental tax rates is suggested. Otherwise, if economic development is the main target, then maintaining the current tax rates is the best choice. 3) For L-H regions, it is recommended to raise environmental tax rates because a higher tax rate would lead to a higher progression of environmental productivity and a lower regression of GDP. 4) For L-L regions, holding the current tax rates is advised if there is no need to reduce emission intensity immediately because both environmental impacts and economic impacts of raising environmental tax rates are tiny.

5. Conclusion

From 2007 to 2012, all regions experience environmental productivity progresses. Southwest region ranks the top in GLPI (valued 0.2101) because of the excellent resource endowment and environmental conditions. While North region is the least progressive region, valued 0.086 in GLPI, due to the conventional economic structure with high energy consumption and high emission. Furthermore, according to the driving factors of environmental productivity, seven regions can be divided into three modes. Northeast region, North region, East coast region, Central region and Northwest region belong to technology dominant mode. Technical improve greatly in these regions because local development strategies encourage them to renovate technology and eliminate backward productive technique. Southwest region belongs to efficiency impeditive mode, indicating that technical efficiency poses a negative effect on environmental productivity progress. Industrial development actions like construction of high emission industrial bases in these regions lead to the regress of technical efficiency. South coast region belongs to co-driven mode. In this mode, technical efficiency change and technology change have similar contributions to environmental productivity progress due to the superior geographical position and abundant capital support for technical innovation and economic structure improvement.

Additionally, according to the effect evaluation of emission charge policies on economy and environment, seven regions can be characterized into four patterns. H-H pattern covers South coast region, indicating both economic impact and environmental impact are at high levels. H-L pattern includes Northeast region and North region, representing the environmental impact is low but the economic impact is high. L-H pattern includes Northwest region and East coast region, which has the opposite meaning with H-L pattern. While, L-L pattern contains Central region and Southwest region, which has the opposite meaning with H-H pattern. Although the degree to which effects of emission charge policies on environment and economy are different in the specific region, the complex effect is positive since the percentage changes of emission intensity in all regions are decline when tightening the emission charge policy.

Nevertheless, there are several limitations of this study. In order to reflect the material flow among various industrial sectors and figure out the impacts of environmental policy on economic production, input-output tables are chosen to be the basic economic dataset. The last two issues of provincial input-output tables of 30 Chinese provinces are in 2007 and 2012, thus, we choose these two years for the analysis. Considering the rapid economic development and changes in production structure, the illustrations would be more accurate using the more recent values if the data is available. Additionally, data related with emission abatement at sector level is incomplete. Thus, we have to assess some environmental variables of each sector based on hypothesis, leading to inaccuracy. Furthermore, material flow of different regions would lead to emission leakage embodied in trade. Future study can be conducted with the consideration of the material flow and emission leakage among multi-regions to figure out the effects of emission charge policy on multi-regional emission leakage and analyze the regional unfairness of emission charge policy.

Acknowledgments

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Supporting information

Table S1 Region category of 30 Chinese provinces

Region	Province	Region	Province
Northeast	Liaoning	South coast	Guangdong
Northeast	Jilin	South coast	Guangxi
Northeast	Heilongjiang	South coast	Hainan

North	Beijing	Central	Henan
North	Tianjin	Central	Hubei
North	Hebei	Central	Hunan
North	Shanxi	Northwest	Shaanxi
North	Inner Mongolia	Northwest	Gansu
East coast	Shanghai	Northwest	Qinghai
East coast	Jiangsu	Northwest	Ningxia
East coast	Zhejiang	Northwest	Xinjiang
East coast	Anhui	Southwest	Chongqing
East coast	Fujian	Southwest	Sichuan
East coast	Shandong	Southwest	Guizhou
East coast	Jiangxi	Southwest	Yunnan

Note: For data available, 30 provinces or cities in China are included, excluding Tibet, Taiwan, Hongkong, and Macao.

Table S2 Sector category and corresponding code

Sector	**Code**	**Sector**	**Code**
Production sectors			
Agriculture	01	Other manufacturing	22
Coal mining	02	Scrap and waste	23
Petroleum and gas	03	Repair service of metal products, machinery and equipment	24
Metal mining	04	Electricity and heat production and supply	25
Nonmetal mining	05	Gas production and supply	26
Food processing and tobaccos	06	Water production and supply	27
Textile	07	Construction	28
Clothing, leather, fur, etc.	08	Wholesale and retailing	29
Wood processing and furnishing	09	Transport, storage and post	30
Paper making, printing, stationery, etc.	10	Hotel and restaurant	31
Petroleum refining, coking, etc.	11	Information transmission, software and information technology	32
Chemical industry	12	Financial intermediation	33
Nonmetal products	13	Real estate	34
Metallurgy	14	Leasing and commercial services	35
Metal products	15	Scientific research and technical services	36
General machinery	16	Management of water conservancy,	37
Specialist machinery	17	Service to households, repair and other services	38
Transport equipment	18	Education	39
Electrical equipment	19	Health and social service	40
Electronic equipment	20	Culture, sports and entertainment	41

Instrument and meter	21	Public management, social security and social organization	42
Emission abatement sectors			
SO_2	43	Cy	51
NO_x	44	Hg	52
SD	45	Cd	53
COD	46	Cr	54
AN	47	Pb	55
P	48	As	56
PP	49	Cu	57
VP	50	Zn	58

Table S3 Taxable pollutions and the corresponding equivalent units

Pollution	Equivalent unit (equivalent/kg)
Air pollution	
Sulfure dioxide (SO_2)	0.95
Nitrogen oxides (NO_x)	0.95
Soot and dust (SD)	3.09
Water pollution	
Chemical oxygen demand (COD)	1
Ammonia nitrogen (AN)	0.8
Phosphorus (P)	0.25
Petroleum pollutants (PP)	0.1
Volatile phenol (VP)	0.08
Cyanide (Cy)	0.05
Aquatic Hg (Hg)	0.0005
Aquatic Cd (Cd)	0.005
Aquatic Cr (Cr)	0.04
Aquatic Pb (Pb)	0.025
Aquatic As (As)	0.02
Aquatic Cu (Cu)	0.1
Aquatic Zn (Zn)	0.2

Table S4 Environmental tax rates of 16 pollutions in 30 provinces

Province	Air pollution (Yuan/ kg-equivalent)			Water pollution (Yuan/ kg-equivalent)												
	SO2	NOx	SD	COD	AN	P	PP	VP	Cy	Hg	Cd	Cr	Pb	As	Cu	Zn
Beijing	12	12	12	14	14	14	14	14	14	14	14	14	14	14	14	14
Tianjin	6	8	6	7.5	7.5	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Hebei	6	6	6	7	7	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6
Shanxi	1.8	1.8	1.8	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1
Inner mongolia	1.8	1.8	1.8	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1
Liaoning	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Jilin	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Heilongjiang	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Shanghai	6.65	7.6	1.2	5	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Jiangsu	4.8	4.8	4.8	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6
Zhejiang	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.8	1.8	1.8	1.8	1.8	1.4	1.4
Anhui	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Fujian	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Jiangxi	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Shandong	6	6	1.2	3	3	1.4	1.4	1.4	1.4	3	3	3	3	3	1.4	1.4
Henan	4.8	4.8	4.8	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6
Hubei	2.4	2.4	1.2	2.8	2.8	1.4	1.4	1.4	1.4	2.8	2.8	2.8	2.8	2.8	1.4	1.4
Hunan	2.4	2.4	2.4	3	3	3	3	3	3	3	3	3	3	3	3	3
Guangdong	1.8	1.8	1.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
Guangxi	1.8	1.8	1.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
Hainan	2.4	2.4	2.4	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
Chongqing	3.5	3.5	3.5	3	3	3	3	3	3	3	3	3	3	3	3	3

Sichuan	3.9	3.9	3.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
Guizhou	2.4	2.4	2.4	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
Yunnan	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Shaanxi	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Gansu	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Qinghai	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Ningxia	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
Xinjiang	1.2	1.2	1.2	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4

2