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作品名称： What comes after picking low-hanging fruits? The transfer direction for environmental regulation policy in China

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What comes after picking low-hanging fruits? The transfer direction for environmental regulation policy in China

Abstract: China faces the dual challenges of economic increasing upward pressure and the continuous deterioration of the environment. In recent years, the state has made remarkable achievements in vigorously rectifying heavy polluted industries with high pollution intensity and large pollution emissions. However, these "low-hanging fruits" that can get good results in short time will be picked up. Based on the panel data, the paper divides 37 industrial sectors into “heavily-”, “middle-”, and “low-” polluted industrial sectors according to “pollution intensive index”. Meanwhile, this paper calculates the green total factor productivity (GTFP) of such three categories with the super-efficiency Hybrid-Distance (Super-EBM), and verifies the influence of three types of environmental regulations on GTFPs with SYS-GMM method. Results show that, firstly, the regulation of the mandatory control environmental regulation (MCR) and market incentive environmental regulation (MIR) have a significant impact on the industrial GTFP, verifying the strong-PH. The voluntary compliance environmental regulation (VCR) has no significant impact on heavily polluted industrial sector. Secondly, the same environmental regulation type has different effects on the three industrial sectors, showing obvious industrial heterogeneity. Thirdly, the effects of different environmental regulations on the same industrial sector are also different. It is necessary to consider synergies and constraints in the process of setting the environment regulation. Fourthly, Middle polluted industrial sectors have a huge room of emission reduction.

Keywords: Green total factor productivity; Environmental regulation intensity; Strong porter hypothesis; Super-EBM;

1. Introduction and background

Chinese government has awared the urgency of implementing environmental regulation[1-2]. According to the 2018 Environmental Performance Index announced by Yale University[3], the score of China was only 50.74, ranking 120th among 180 countries and regions in the world (see Fig.1).However, due to the inherent inadequacy of the country's ecological environment and the rigid constraints on economic growth, the interaction between environmental protection and industrial development is more prominent in China in comparison to other countries[4].

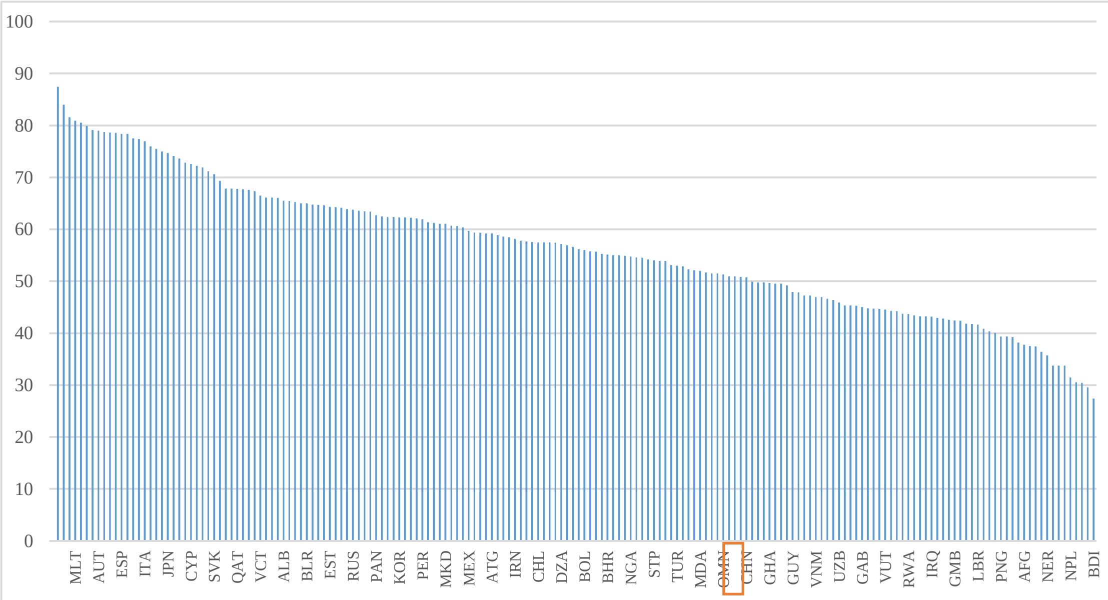

Fig.1 Environmental performance index score in 2018

In the context of the worsening environment, China has proposed that the mode of economic growth must be transformed from unsustainability to sustainability and launched a full range of actions[5]. Most of the energy saving measurements had been carried out in industry sector. Since 2006 there has been a mandatory energy savings programme for the largest enterprises, with targets for energy-intensive industry and financial support through a dedicated government-backed fund. The Chinese government also introduced an energy saving obligation programme for the Top 1000 enterprises in nine energy intensive industries during 2006-2010. These enterprises accounted for 33% of the country’s total energy consumption and 47% of industrial energy consumption in 2005. The energy efficiency becomes part of performance evaluation for managers in the state-owned companies. Overall, the programme has saved 165 Mtce, representing 183% of the original target[6]. The scope of this programme was extended to the Top 10 000

Programme in 2011. A total of 14 641 enterprises are now regulated with an energy savings obligation. After that, over the period of 2006 to 2014, the Chinese central government has shut down 95630 MW of power production capacity, 930 million tons of cement production capacity, and 147.8 million tons of steel production capacity. The targeted industries also expand to almost the whole economy. By the end of 2014, the Top 10 000 programme has already saved 309 Mtce annually, about 20% more than the target of 250 Mtce[7]. Here, all of them are called “Low fruit first pick” strategy.

Such mode of environmental regulations are leaded by the government with a mandatory control approach. Simultaneously, market policies and informal regulations are also proved to be extremely important in deployment of clean energy in China[8]. Then, some pressing questions are posed within both the academic and management context: What is the condition of the industrial sectors after the series of administrative measures? What is the focus of the next reform after the “low-fruit first pick” policy? And do different industries need different treatments? The overall goal of this paper is to answer these questions above.

2. Literature Review

2.1 Porter hypothesis in literatures

In 1991, Porter and his colleagues put forward the idea that appropriate environmental regulation could encourage domestic enterprises to research and adopt eco-innovation, so as to gain a competitive advantage in the green market[9]. Porter hypothesis (PH) put forward challenges to the traditional neoclassical economics theory in the theoretical framework of environmental protection related issues, and provided a new perspective for exploring the relationship between environmental protection and corporate development.

Jaffe & Plamer[10] proposed that the PH could be divided into Narrow-PH, Weak-PH and Strong-PH. Narrow-PH points out that flexible regulation provides a strong incentive for innovation than regular regulation. Narrow-PH believes that flexible regulatory policies, especially economic instruments, can stimulate enterprise innovation and are more effective than traditional regulatory forms. Weak-PH indicates that appropriate environmental regulation may stimulate innovation. Weak-PH announces that reasonable environmental regulation can stimulate innovation, but whether the innovation is good or bad is not sure. Regarding the related researches, majority of the academic communities had verified the existence of Weak-PH, and reached an agreement that appropriate environmental regulations can promote technological innovation of enterprises[11-14].

Strong PH holds that environmental regulation can not only stimulate enterprise innovation, but also improve the competitiveness of enterprises (shown in Fig.2). Unlike the relative agreement in the research of Weak-PH, the evidences is more mixed for the Strong-PH[15-17]. Early studies focused on the US and concluded that environmental regulation caused a productivity slowdown[18-20]. More recently, more and more researchers find positive results[21-24]. Due to the different angles, methods and data selected by various research scholars, the research conclusions are not the same. Most of the existing Strong-PH literatures are considered from the national, regional and other aspects[25-26], some scholars have also verified the single industry[27-28]. Meanwhile, many researchers have shown that the impact of environmental regulation on competitiveness is not absolute, and the relationship between environmental rules and competitiveness might be ‘U’-shaped[29], ‘inverted U’-shaped[30], or ‘inverted N’-shaped[31]. The research results were so diverse that if simply verify the Strong-PH from national or inter-provincial level, and ignore the characteristics of each industry, will make the conclusions lack of flexibility. In that case, classifying industries and studying the relationship between individuals has more practical significance for verifying the Strong-PH, national policy formulation and industrial regulation.

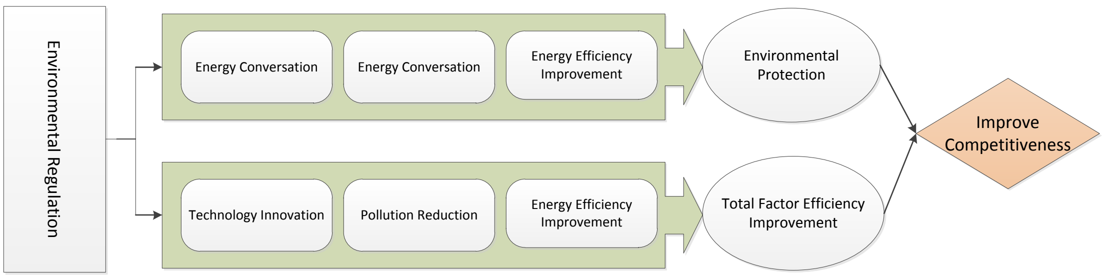

Fig.2 Structure of strong-PH

There is currently some literatures from industrial perspective. Li & Tao[28] divided the 28 manufacturing industries into three categories: heavy, medium and light polluted industries. Results showed that the environmental pollution intensity and TFP of heavy polluted industries are ‘U-shape’ while such cases of medium and light polluted industries are ‘inverted U-shape. Yuan et al.[32] examined manufacturing industry’s data from 28 subsectors from 2003 to 2013 in China and found that as environmental regulation was not reasonable enough, it could not increase ecological efficiency yet. Meng et al.[33] indicated that micro, small and medium-sized enterprises (MSMEs) produced 53% of China’s CO_2 emissions in 2010. Liu & Zhao[34] established the industrial carbon intensive index to divide 36 sectors of industries into different kinds of carbon intensive industries, and found that Strong-PH has industrial heterogeneity in different industrial sectors. At the same time, this research considered that the medium carbon intensive industry should to give enough attention.

Generally, the existing researches on the Strong-PH mainly focus on regional panel data analysis, and there are few researches on industrial industry segmentation, and the basis for division is not so comprehensive for decision making. The main reason is that, with different business background of those different sectors, the cost of technological innovations and the difficulty of industrial upgrading differs from one to another. Therefore, there are great differences on the attitudes toward environmental regulation policies in different industrial sectors. On the other way, as the focus and implementation of different environmental regulations vary from one to another, which leads to different attitudes to its response. Simultaneously, “low-hanging-first-pick” strategy, can promote the realization of China's energy-saving and emission reduction targets in the short term, but no one knows how to achieve the subsequent energy-saving emission reduction targets after the “low-fruits” are removed.

2.2 Environmental regulation

In the 1970s, due to the influence of a wide range of industrial pollution, the United States, the United Kingdom and other Western countries began to formulate relevant laws and regulations for environmental protection, which opened the curtain of modern environmental regulation[35]. It’s called mandatory control environmental regulation (MCR) which is government-lead and law-based. Berman[21] selected the manufacturing industry in the United States to research, finding that the laws and regulations on air pollution forced companies to adopt emission reduction measures and also increased business productivity.

With the deeply integrated of the global market, market incentive environmental regulation (MIR) began to take shape in the early 1990s, which focused on polluter burdens for environmental policy development, such as environmental tax and permission trading system. The academic community generally refers to MCR and MIR as formal environmental regulations. López-Gamero et al.[36] compared MCR with MIR and concluded that MIR contributes more to the improvement of industrial competitiveness than MCR.

In recent years, with the increasing complexity of environmental issues and consumers' awareness of environmental protection and resource conservation, environmental regulations have gradually become constrained by self-feature, promoting a new generation of environmental regulation that is diversified and informal[37] Such environmental regulations are based on the interests of social groups themselves is called informal environmental regulations. Pargal and Wheeler[38] believed that social groups and industries would negotiate with each other to promote energy conservation and emission reduction when formal regulatory policies were invalid or missing. Lim and Prakas[39] selected ISO14001 as an assessment indicator for voluntary compliance environmental regulation (VCR), suggesting that the impact of VCR on corporate innovation should be fully considered.

From the government-lead to market and voluntary-driven perspectives, environmental regulations tend to be more and more complicated nowadays. It is unrealistic to implement an optimal environmental regulation to assess the total factor productivity (TFP) for a certain region or sector. Therefore, according to different environmental regulations which the effects for green total factor productivity are different, it is necessary to explore and find the optimal combination between the environmental regulation and the current industrial development. It must has more realistic research significance.

In view of this, this paper selects the panel data of 37 industries in China from 2003 to 2015, calculates the GTFP of industrial industry based on Super EBM-GML index. After that, three kinds of environmental regulation measurements (MCR, MIR and VCR) are applied to verify the relationship between environmental regulation and GTFP. The contribution of this paper is three-fold. Firstly, 37 polluted industrial sectors are classified into high, middle and low polluted industrial sectors according to pollution degree and pollution intensity. In this paper, the total sewage volume (environmental tax) rather than the scale of carbon emission is chosen to measure the pollutant level of each industrial sectors, in order to avoid the calculation distortion between different pollutants. Secondly, to take both the regulation stringency and instrument design into consideration. The paper divides environmental regulations into three types: mandatory control regulation, market incentive regulation and voluntary compliance regulation, and examines whether there appear to be heterogeneous effects on different polluted industrial sectors under different types of environmental regulations. Finally, based on the results above, the paper represents a better understanding and some reasonable perspectives of “low-fruits-first-pick” dilemma.

The rest of the paper is organized as follows: Section 3 is the classification of polluted industrial sectors in China. Section 4 calculates the regulation level of three kinds of environmental regulations measurements. Section 5 presents the GTFP of high, middle and low polluted industrial sectors since 2004 to 2015. Based on the results above, the test of Strong-PH is given and the threshold of such three kinds of polluted industrial sectors under three different environmental regulations measures are presented in Section 6. Finally, Section 7 concludes the whole study and give some policy implications.

3. Classification of polluted industrial sectors

With different characteristics, the effects of different industrial sectors caused by environmental regulations vary from one to another. In view of this, before measuring the GTFPs of different industrial sectors, we have to firstly classify China's industrial sectors according to their different pollutant discharge conditions.

3.1 Description of polluted industrial sectors

According to the Industrial Classification for National Economic Activities (2017) published by the National Bureau of Statistics (NBS), China's industry is divided into 41 industry types. However, as the major adjustments made by NBS in 2010, some of the industries were eliminated, merged, or split. In that case, to ensure the continuity and effectiveness of the data, some industrial sectors without sufficient data sets will not mentioned in this research[1]. Finally, 37 industries are selected.

3.2 Basis of classification of polluted industrial sectors

It is easy to understand that, due to the representativeness of indicators, the incompatibility of pollutants, and the heterogeneity of industrial sectors, we need the measurements to calculate the pollutant conditions which can avoid the comparation dilemma of different pollutants. Considering that, emission scales of major pollutants, environmental tariff, and emission intensity are set to measure the polluted conditions of different industrial sectors.

[1] In this paper, 4 industries were eliminated. They are: “Metal products machinery and equipment repair industry”, “waste resources comprehensive utilization industry (which is called ‘waste materials recycling industry’ before 2010)”, “Mining auxiliary activity industry”, and “other manufacturing industry”. The “Rubber products industry” and the “Plastic products industry” before 2010 (including) were merged into the “Rubber and plastic products industry”. The transportation equipment manufacturing industry before 2010 (including 2010) will be split according to the proportion of automobile manufacturing and railway ship aerospace and other transportation equipment manufacturing industries after 2010.

3.2.1 Emission scales of major pollutants

E_{ij}[2] stands for the emission scales of major pollutants. Considering that the total amount of waste water, gas, and solid ignore the specific pollutants, some major pollutant indicators from environmental monitors are calculated. Chemical oxygen demand (COD) and Ammonia-Nitrogen Emissions (ANE) are used for waste water, sulfur dioxide (SO_2), soot emissions, and dust emissions are major waste gas, and the general industrial solid waste and hazardous waste output are the main solid waste.

3.2.2 Environmental tax

Due to the incompatibility of different pollutants, a certain weighting method cannot measure the hazard degree of each pollutant. “Environmental Protection Tax Law of the People's Republic of China” (Hereinafter referred to as the "Environmental Tax Law") has come into force since Jan. 1, 2018. As the “Environmental Tax Law” almost comprehensively covers the taxation standards for most pollutants, it can achieve the comparability of various pollutants. In that case, it is feasible to convert the discharge of major pollutants into environmental taxes. In that case, the standards of the environmental tax for different pollutants in “Environmental Tax Law” are used to calculate the taxes of industrials since 2003 to 2015.

To calculate the degree of pollution hazard, we have to first calculate the total amount of pollutant. Calculation formula is as follows:

$$C_i = \sum\left[\left(E_{ij} \times T_j\right) / PE_j\right] + E_{GS} \times T_{GS} + E_{DS} \times T_{DS} \quad (i = 1, 2, ..., 37) \qquad (1)$$

Here, C_i is the pollutant scales of the *ith* industry, E_{ij} stands for the emission scales of the *jth* pollutant (including COD, ANE, SO_2, soot, dust) in the *ith* sector. Tj is the environmental tax of pollutants, PE_j is the equivalent value of pollutants. E_{GS} and E_{DS} stand for the emissions of general solid wastes and hazardous wastes, T_{GS} and T_{DS} stand for the pollute taxes of general solid wastes and hazardous wastes. As solid waste doesn’t need equivalent calculation, it will be calculated separately[3].

[2] Here, i stands for the ith sector, and j stands for the jth pollutant.

[3] According to the “Environmental tax law”, the tax amount is interval value, and the paper selects the median value for calculation.

Table 1 Standards of environmental tax for different pollutants

Pollutant types	Pollutant name	Equivalent pollutant	Tax
Water pollutants	COD	1kg	7.7 Yuan/Equivalent pollutant
	ANE	0.8 kg	
Atmospheric pollutants	SO_2	0.95 kg	6.6 Yuan/Equivalent pollutant
	Soot	2.18 kg	
	Dust	4 kg	
Solid waste	General solid waste	/	15 Yuan/ton
	Danger solid waste	/	1000 Yuan/ton

Source: *Environmental Tax Law of the People's Republic of China; Environmental Statistics Yearbook of China*.

3.2.3 Pollution intensive index

Based on the emission scales of major pollutants and the environmental tax calculated above, the pollution intensive index of each industries will be measured. Most of the existing researches evaluate the severity of pollution of industries from the emission scales while neglect the emission intensity of pollutants[2, 28]. Meanwhile, as the total amount of emissions cannot be directly added, most researches focused on certain type of pollutant[40]. In this paper, the severity of pollution of industries will be calculated from two aspects, pollution degree and pollution intensity. Pollution degree means the proportion of pollutants discharged by various industries to the total amount of emissions, and pollution intensity stands for the pollutant emissions per unit of industrial output value. The calculation processes of such two parts are as follows.

- ***Pollution degree.*** Suppose that PD_i is the pollution degree of the *ith* industry. As shown in Eq.(2), PD_i means the proportion of pollutants discharged by various industries (C_i) to the total amount of emissions ($\sum C_i$, here are 37 industries selected in this research).

$$PD_i = \frac{C_i}{\sum_{i=1}^{n} C_i} \qquad (n = 37) \tag{2}$$

- ***Pollution intensity.*** Suppose that PI_i is the pollution intensity of each industries. According to Eq. (3), C_i is the pollutant scales of the *ith* industry, and V_i is the industrial output of each industries.

$$PI_i = \frac{C_i}{V_i} \qquad (i = 1, 2, 3 \cdots 37) \tag{3}$$

- ***Pollution intensive index.*** As there are different units in pollution degree and pollution intensity, we have to first pre-process these data as follows:

$$PD_i^{'} = \frac{PD_i - \min(PD_i)}{\max(PD_i) - \min(PD_i)} \quad (i = 1, 2, 3 \cdots 37) \tag{4}$$

$$PI_i^{'} = \frac{PI_i - \min(PI_i)}{\max(PI_i) - \min(PI_i)} \quad (i = 1, 2, 3 \cdots 37) \tag{5}$$

After that, pollution intensive index I can be calculated as the geometric mean of both pollution degree and pollution intensity, which is shown in Eq. (6).

$$I_i = \sqrt{PD_i^{'} \times PI_i^{'}} \quad (i = 1, 2, 3 \cdots 37) \tag{6}$$

3.3 Classification of polluted industrial sectors

With the Eq.(1) to Eq.(6), the pollution intensive indexes of 37 industries are displayed in Fig.3 in the order from the biggest to the smallest, the bigger the scatter, the severer pollutant condition of this industry, vice versa. To explain the extent to which environmental regulations affect different types of industries in detail, 37 industries are classified into high ($I_i \geq 0.115$), middle ($0.010 \leq I_i \leq 0.082$) and low ($I_i \leq 0.009$) polluted industrial sectors based on k-means clustering algorithm. Results are shown in Table 2.

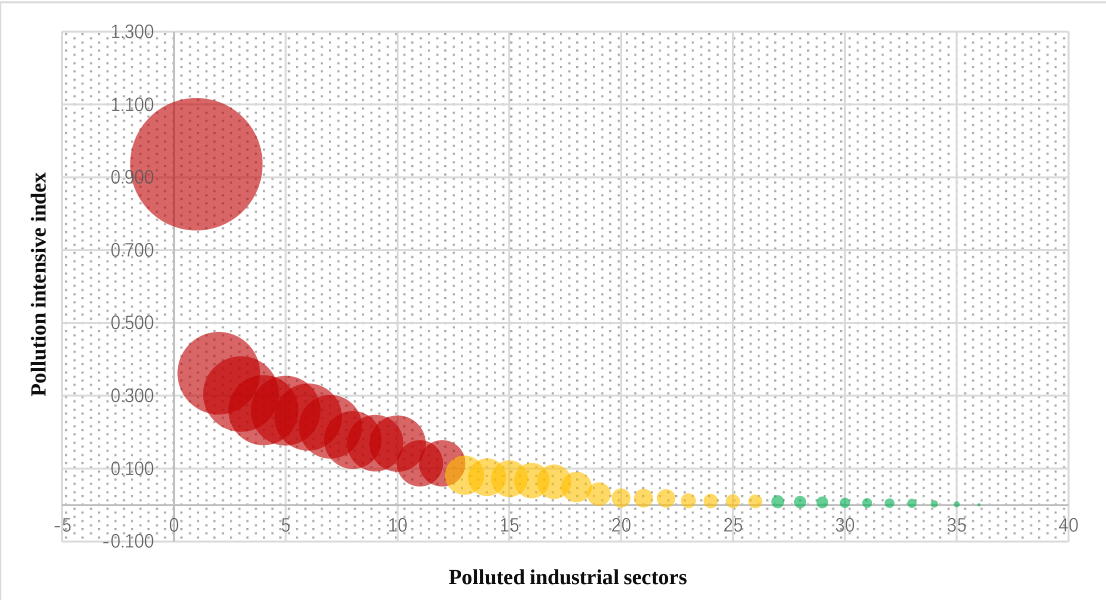

Fig.3 Scatter map of pollution intensive index of 37 polluted industrial sectors

There are some interesting results in Table 2. First of all, the most seriously polluted industries are still concentrated in resource extraction, chemical manufacturing and paper industry, with high pollution intensity. Nine of the Top 10 strongest pollution intensity industries are in the high polluted industrial sectors, expect the “Other Mining Industry

(L10)". When we come to the "Other Mining Industry", it is clearly that the pollution intensity of "Other Mining Industry" is the highest one, however, as its pollution scale is very small, almost negligible (0.000), the pollution intensive index of "Other Mining Industry" is still low and then be classified into the low polluted industrial sectors. Such conclusion also proves the importance and necessity of measuring pollution intensive index with both pollution degree and pollution intensity at the same time.

Table 2 Classification of 37 polluted industries

Classification	Industrial sector	Pollution degree	Pollution intensity	Pollution intensive index
High polluted industrial sectors ($I \geq 0.115$)	Production and Supply of Electric Power and Heat Power (H1)	1.000	0.875	**0.936**
	Manufacture of Paper and Paper Products (H2)	0.191	0.685	**0.362**
	Manufacture of Non-metallic Mineral Products (H3)	0.292	0.318	**0.305**
	Smelting and Pressing of Ferrous Metals (H4)	0.314	0.216	**0.260**
	Mining and Processing of Non-ferrous Metal Ores (H5)	0.085	0.788	**0.259**
	Manufacture of Raw Chemical Materials and Chemical Products (H6)	0.286	0.204	**0.242**
	Mining and Processing of Ferrous Metal Ores (H7)	0.082	0.565	**0.215**
	Smelting and Pressing of Non-ferrous Metals (H8)	0.159	0.200	**0.178**
	Mining and Processing of Non-metal Ores (H9)	0.049	0.588	**0.170**
	Production and Supply of Gas (H10)	0.045	0.635	**0.169**
	Processing of Petroleum, Coking, Processing of Nuclear Fuel (H11)	0.104	0.127	**0.115**
	Mining and Washing of Coal (H12)	0.083	0.158	**0.115**
Middle polluted industrial sectors ($0.010 \leq I \leq 0.082$)	Processing of Food from Agricultural Products (M1)	0.084	0.080	**0.082**
	Manufacture of Chemical Fibers (M2)	0.030	0.197	**0.076**
	Manufacture of Wine, Drinks and Refined Tea (M3)	0.038	0.137	**0.072**
	Manufacture of Textile (M4)	0.060	0.075	**0.067**
	Manufacture of Medicines (M5)	0.038	0.105	**0.064**
	Manufacture of Foods (M6)	0.029	0.085	**0.049**
	Manufacture of Metal Products (M7)	0.024	0.038	**0.030**
	Manufacture of Leather, Fur, Feather and Related Products and Footwear (M8)	0.010	0.039	**0.019**
	Extraction of Petroleum and Natural Gas (M9)	0.010	0.034	**0.019**
	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products (M10)	0.008	0.040	**0.018**
	Manufacture of Rubber and Plastic Products (M11)	0.009	0.015	**0.012**
	Manufacture of Computers, Communication, and Other Electronic Equipment (M12)	0.016	0.007	**0.011**
	Manufacture of Railway, Shipbuilding, Aerospace and Other Transportation Equipment (M13)	0.006	0.018	**0.011**

	Printing, Reproduction of Recording Media (M14)	0.003	0.032	**0.010**
Low polluted industrial sectors (I_i≤0.009)	Production and Supply of Water (L1)	0.001	0.056	**0.009**
	Manufacture of General Purpose (L2)	0.009	0.007	**0.008**
	Manufacture of Textile Wearing and Apparel (L3)	0.005	0.012	**0.008**
	Manufacture of Tobacco (L4)	0.002	0.013	**0.006**
	Manufacture of Special Purpose Machinery (L5)	0.005	0.006	**0.005**
	Manufacture of Automobile (L6)	0.007	0.004	**0.005**
	Manufacture of Measuring Instrument (L7)	0.002	0.011	**0.005**
	Manufacture of Furniture (L8)	0.001	0.009	**0.003**
	Manufacture of Electrical Machinery and Equipment (L9)	0.004	0.001	**0.002**
	Other Mining Industry (L10)	0.000	1.000	**0.001**
	Manufacture of Articles for Culture, Education and Sport Activity (L11)	0.000	0.000	**0.000**

Data Source: *Calculated with China Statistical Yearbook on Environment (2004-2016) & China Statistical Yearbook (2016).*

4. Evaluation of environmental regulation in China

4.1 Mandatory control environmental regulation

The intensity of the MCR (ER_{MCR}) will be measured as the ratio of the operating cost of wastewater and waste gas (OC) from the industrial sectors to the corresponding industrial sectors' output value (OV)[4]. It can be valued with Eq. (7). The higher the value of ER_{MCR}, the greater the MCR.

$$ER_{MCR} = \frac{OC}{OV} \tag{7}$$

The value of MCR is shown in Fig.4. For ease of reading, only the results of the year 2003, 2009, and 2015 are listed.

[4] Data source of operating cost of wastewater and waste gas: China Statistical Yearbook on Environment (2004-2016);

Data source of industrial sectors' output value: National Bureau of Statistics.

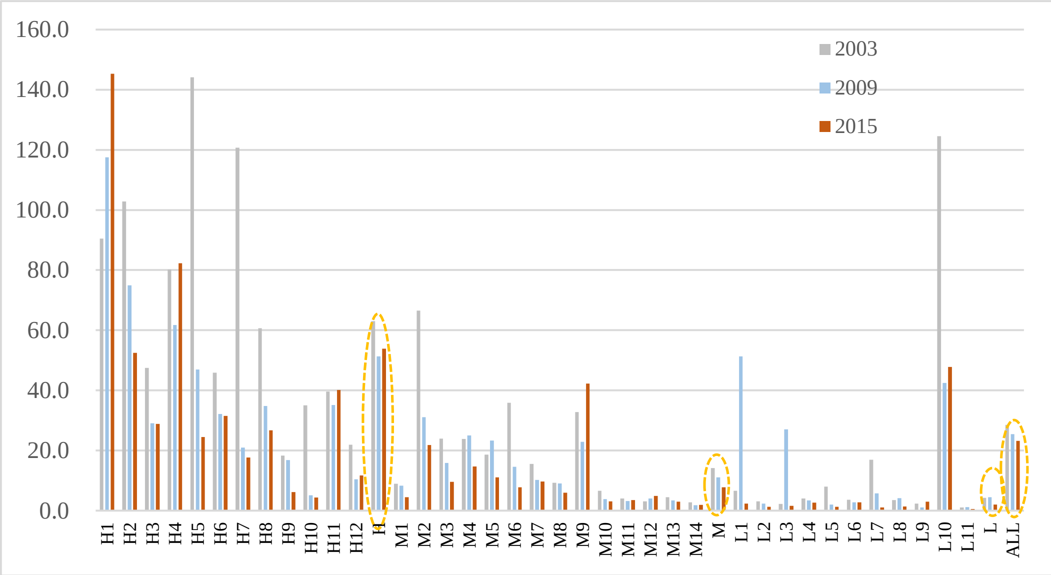

Fig.4 The situation of MCR in China's industrial sectors

It is clearly shown in Fig.4 that, during the research period, almost majority of the MCRs are imposed in the high polluted industrial sectors, except "Other mining industry (L10)". The order of the intensity of the environmental regulations is "high-middle-low" polluted industrial sectors. That is to say, high polluted industrial sectors are still the most important objects to the central government for energy conservation and emission reduction. When we come to the timeline, the average intensity of the MCR has decreased year by year (see the data "ALL" at the end of Fig.4). However, the situation varies in certain industry. For example, the intensity of the MCR in H1 is increasing year by year. H1 is the most polluting industry, although the strength of the MCR is now weaken, the most serious polluted industrial sectors are still the focus of the policy.

4.2 Market incentive environmental regulation

According to the researches of Ma et al.[41] and Wang &Qi[42], the comprehensive energy prices of industries (ER_{MIR}) are used to represent the MIR. It is calculated as the ratio of energy costs (EC) to total energy consumption (TC)[5], see Eq. (8).

$$ER_{MIR} = \frac{EC}{TC} \tag{8}$$

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[5] Data source of energy price: China Price Yearbook (2006-2015);

Data sources of industrial ex-factory price index for coal mining and washing industry, the industrial ex-factory price index for oil and natural gas extraction industry, the electric power production and the industrial ex-factory price index for the supply industry: The National Bureau of Statistics;

Other data sources: China Statistical Yearbook (2005-2017), China Energy Statistics Yearbook (2004-2016).

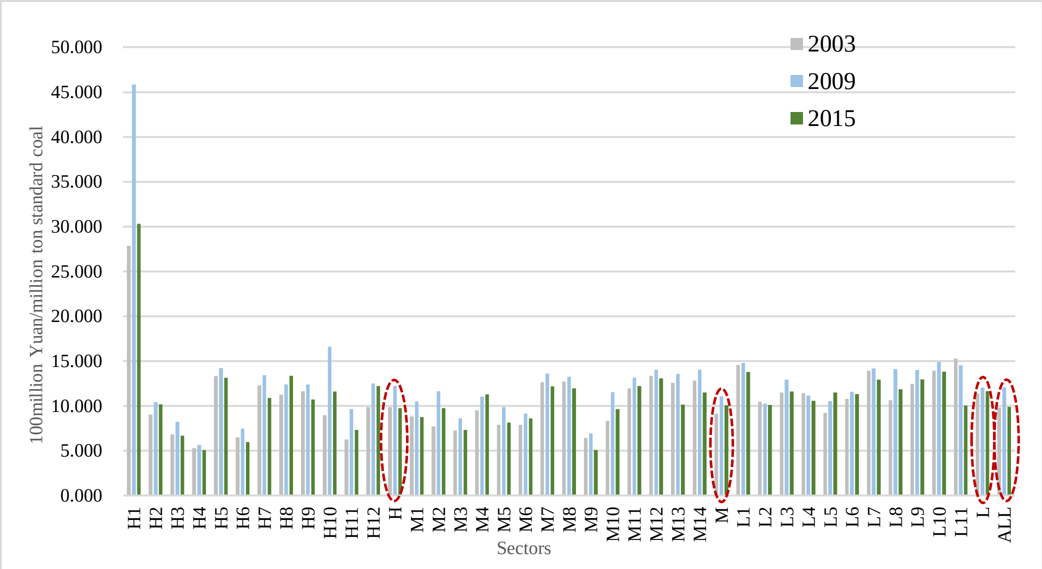

Fig.5 The situation of the MIR in China's industrial sectors

Results of the MIR in China's industrial sectors are shown in Fig.5. As we can see from Fig.5 that, the intensity of the MIR in each industrial sectors are almost the same, except H1. It means that the MIR is comparative equilibrium in most of the industrial sectors and H1 is still a focus in the MIR. On the other hand, it is clearly that the regulation in 2009 is somewhat higher than 2003 and 2015. The reason is that after the economic crisis broke out in 2008, the energy price reform taken place in China. From then on, energy price reform accelerated the MIR.

4.3 Voluntary compliance environmental regulation

Environmental Management System (EMS) is widely recognized as a standardized voluntary compliance implementation committee all over the world[43]. Among EMS, the ISO14001 standard has become an effective incentive mechanism for enterprises to improve the use efficiency of their production materials, better fulfill the government's environmental protection tasks, and obtain financial subsidies and preferential policies from the government to make up for the green of enterprises. In that case, ISO14001 is always considered to be a measure of the VCR for enterprises and is widely used by scholars[44-45].

The EMS data mentioned in this paper is derived from the China National Accreditation Service for Conformity Assessment. The amount of EMS sheets in 34 industries[6] from 2004 to 2015 is separated from the main business income of the

[6] The classification standards of "Domestic Economic Industry Classification 2017" is somewhat different from the industries mentioned in Section 3. Some industries will be differentiated or merged, the industry of "black metal smelting and rolling processing industries", "non-ferrous metal smelting and rolling processing industry" and "special

corresponding industry (main business income data from the National Bureau of Statistics), and the intensity of the VCR is obtained with Eq. (9).

$$ER_{VCR} = \frac{EQ}{OR} \tag{9}$$

Here, ER_{VCR} indicates intensity of the VCR, EQ is the amount of ISO14001 sheets, and OR is the main business income. Results are shown in Fig. 6. From the average point of view, the intensity of the VCR is increasing year by year, whether it is high, middle, or low polluted industrial sectors. However, for different industries, the degree of their spontaneous varies widely. Generally speaking, the degree of the VCR in low- and middle-polluted industrial sectors is significantly higher than that in high polluted industrial sectors.

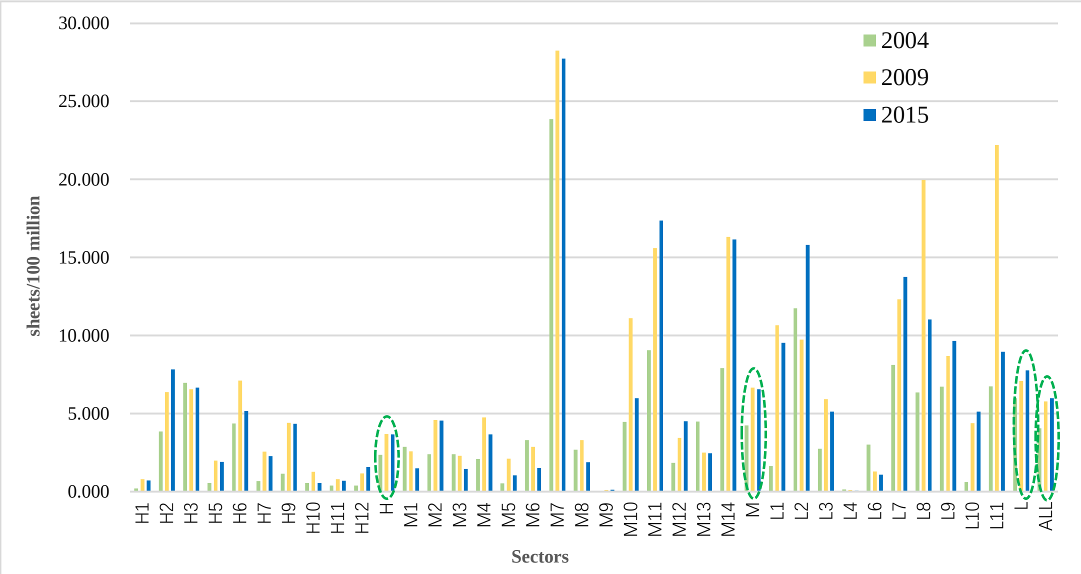

Fig. 6 The situation of the VCR in China's industrial sectors

5. GTFP of three kinds of polluted industrial sectors

5.1 Super-efficient hybrid distance function

Data envelopment analysis (DEA) is common used to calculate GTFP for scholars. However, single radial model or non-radial measure has several shortcomings[46]. Considering that, Tone & Tsutsui[47] proposed a new hybrid distance function—Epsilon-based measure (EBM), which can combine the merits of radial and non-radial models together. For one thing, the model can effectively reflect the radial ratio between the input target value and the input real value. For another, EBM model can reflect the differences between the non-radials of each input and output variable, which can reflect the relative

equipment manufacturing industries" were eliminated. Finally, 34 industries are selected.

efficiency of the evaluation unit more accurately. In view of this, EBM will be used to calculate the efficiency of green technology. The production-oriented EBM model is organized as follows:

$$\gamma^* = \min \frac{1}{\varphi + \varepsilon^+ \frac{1}{\sum_{r=1}^{q} w_r^+} \sum_{r=1}^{q} \frac{w_r^+ s_r^+}{y_k}}$$
$$s.t. \begin{cases} X\lambda \le x_k \\ Y\lambda - \varphi y_k - s^+ = 0 \\ \lambda \ge 0 \\ s_r^+ \ge 0 \end{cases} \tag{10}$$

Where ε^+ $(0 \le \varepsilon^+ \le 1)$ is a key parameter which is related to the non-radial φ and the radial slacks terms. Suppose that w_r^+ represents the degree of relative importance of output r, $\sum_{r=1}^{q} w_r^+ = 1 (w_r^+ \ge 0)$, and $0 \le \gamma^* \le 1$. If we set $\varepsilon^+ = 1$, it selects the output-oriented Slack Based Measure (SBM) model, and if $\varepsilon^+ = 0$, it stands for the output-oriented CCR model.

The count of ε^+ and w_r^+ is based on the diversity index and affinity index. Identify that vectors a and b as shadow values of output indexes of DMUs[7]. Then, the affinity index can be calculated by diversity index as follows:

$$S(\mathbf{a},\mathbf{b}) = 1 - 2D(\mathbf{a},\mathbf{b}) \tag{11}$$

The rules of affinity index $S(\mathbf{a},\mathbf{b})$ are:

$(1) S(\mathbf{a},\mathbf{a}) = 1 (\forall \mathbf{a})$ – Identical, $(2) S(\mathbf{a},\mathbf{b}) = S(\mathbf{b},\mathbf{a})$ – Symmetric,
$(3) S(t\,\mathbf{a},\mathbf{b}) = S(\mathbf{a},\mathbf{b}) (\forall t > \mathbf{a})$ – Units–invariant $(4) 1 \ge S(\mathbf{a},\mathbf{b}) \ge 0 (\forall \mathbf{a},\mathbf{b})$

The calculation process of diversity index is:

$$D(\mathbf{a},\mathbf{b}) = \begin{cases} \dfrac{\sum_{j=1}^{n} |c_j - \bar{c}|}{n(c_{\max} - c_{\min})} & (\text{if } c_{\max} > c_{\min}) \\ 0 & (\text{if } c_{\max} = c_{\min}) \end{cases} \tag{12}$$

$$c_j = \ln \frac{b_j}{a_j} \quad (j = 1, \cdots, n),$$
$$\bar{c} = \frac{1}{n} \sum_{j=1}^{n} c_j, \tag{13}$$
$$c_{\max} = \max(c_j) \text{ and } c_{\min} = \min(c_j)$$

Then, the parameters of EBM can be calculated with the matrix of diversity index:

[7] Hypothesis that, there are two output indexes in this EBM model.

$$\varepsilon = \frac{m - \max(\rho)}{m-1}$$
$$w_i = \frac{v_t}{\sum_{i=1}^{m} v_t} \tag{14}$$

Parameter ρ is the largest eigenvalue of S which associated nonnegative eigenvector $\boldsymbol{v}$.

It is a common phenomenon that several DMUs to be evaluated as valid in EBM models (that is, the efficiency values of several DMUs is 1). Therefore, we established VRS (Variable Returns to Scale) based on EBM and included undesirable-output super efficiency model: Super-EBM model[48]. The definition of Super-EBM is as follows:

$$\gamma^* = \min \frac{1}{\varphi + \varepsilon^+ \frac{1}{\sum_{r=1}^{q} w_r^+} \sum_{r=1}^{q} \frac{w_r^+ s_r^+}{y_k}}$$
$$s.t.\begin{cases} \sum_{\substack{j=1 \\ j \neq k}}^{n} \lambda_j x_{ij} \le x_{ik} \\ \sum_{\substack{j=1 \\ j \neq k}}^{n} \lambda_j y_{ij} + s_r^+ \ge y_{rk} \\ \sum_{\substack{j=1 \\ j \neq k}}^{n} \lambda_j = 1 \\ \lambda \ge 0, s_r^+ \ge 0 \end{cases} \tag{15}$$

5.2 Global Malmquist-Luenberger index

Even though the geometric mean form of the Malmquist-Luenberger (ML) index has long been used in measuring environmentally sensitive productivity growth, one of its drawbacks is that it is not circular. The conventional ML index also has a possibility of having an infeasibility problem. In order to overcome these weaknesses of the ML index, we proposed an alternative index in this paper, called the global Malmquist-Luenberger (GML) index. The GML index was created by Pastor and Lovell in 2005[49], which stands for the growth rate of GTFP and combines with EBM model which involves undesirable output to resolve GTFP. Existing researches have disassembled the GML index into two dimensions[50-51]: the technical efficiency change (EC) represents the change of DMUs' technical efficiency in two periods, and the technological change (TC) is related to production technology. The GML index is defined as follows:

$$
\begin{aligned}
GML^{t,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) &= \frac{1+D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}{1+D^G\left(x^t, y^t, b^t\right)} \\
&= \frac{1+D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}{1+D^t\left(x^t, y^t, b^t\right)} \times \\
&\quad \left(\frac{\left(1+D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right) / \left(1+D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)}{\left(1+D^G\left(x^t, y^t, b^t\right)\right) / \left(1+D^t\left(x^t, y^t, b^t\right)\right)}\right) \\
&= \mathrm{EC}^{t,t+1} \times \mathrm{TC}^{t,t+1}
\end{aligned} \tag{16}
$$

Where b^t is undesirable output of DMU at the t period. The distance function as follows:

$$
D^t\left(x^t, y^t, b^t\right) = \max\left\{\beta : \left(y + \beta y, b - \beta b\right) \in P^t\left(x^t\right)\right\} \tag{17}
$$

Here, 37 industries panel data in China from 2003 to 2015 are gathered to evaluation the GTFP values. The detailed descriptions of the data used are listed in Table 3.

Table 3 Data description

Category	Index	Description	Data source
Input	Capital input	Net value of fixed assets[8]	➢ China Statistical Yearbook ➢ China Industry Statistical Yearbook ➢ China Energy Statistical Yearbook ➢ China Economic Census Yearbook ➢ National Bureau of Statistics
	Labor input	Average annual number of employees in all industrial sectors over the years[9]	
	Energy input	Total energy consumption of all industrial sectors over the years	
Output	Desirable output	Industrial sales value[10]	
	Undesirable output	Total amount of waste water, waste gas and waste solid	

5.3 Evaluation of GTFP in three kinds of polluted industrial sectors

In this paper, the GML index is measured by MaxDEA7-Ultra. In the process of measurement, the rate of change of two years is required, and one degree of freedom is lost. Therefore, the obtained GML index is from 2004 to 2015.Assuming that the GTFP is 1.000 in 2003, GTFP in 2004 equals the GTFP value of 2003 multiplies the GML value in 2004[52], and so on. GTFP values of three kinds of polluted industrial sectors are calculated in Fig.7.

8 The net value of fixed assets was reduced to the constant price in 2003.

9 Due to the loss of the average number of employees in 2012, it was supplemented by linear interpolation.

10 The GDP deflator is based on 2003.

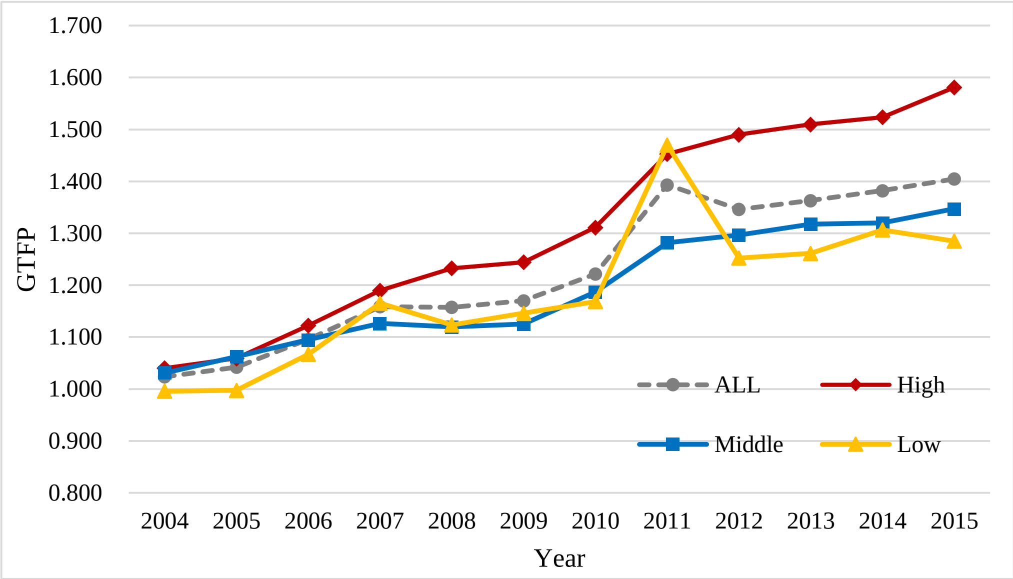

Fig.7 Values of GTFP of three kinds of polluted industrial sectors

As can be seen from Fig.7 that, the average GTFP growth rate in polluted industrial sectors increased from 1.024 in 2004 to 1.405 in 2015. There are two significant increasing periods during the entire study period: 2005-2007 and 2009-2011. In the opening stage of both “Eleventh Five-Year Plan” and the “Twelfth Five-Year Plan”, various environmental protection policies have effectively controlled the discharge of pollutants, which makes GTFP promote significantly. From the perspective of each polluted industrial sectors, high polluted industrial sector is the only one whose GTFP performs better than that of the whole industry, followed by middle and low polluted industrial sectors. On another hand, GTFP of high and middle polluted industrial sectors showing a steady upward trend, the development of high polluted industrial sectors’ GTFP has always developed at a high speed since 2005. It can be inferred that, under the focus of the national system on high polluted industrial sectors, GTFP of high polluted industrial sectors has been greatly improved. However, GTFP has a slower development rate in middle and low polluted industrial sectors, especially middle polluted industrial sectors. Therefore, it is a great way to improve the GTFP of middle polluted industrial sectors to enhance GTFP of whole industry.

6. Heterogeneous test of environmental regulations on GTFP

6.1 SYSGMM modelling and data description

SYSGMM is a dynamic panel data regression method proposed by Blundell & Bond[53], which can improve the efficiency of estimation, and it is widely used in the field of Strong-PH. This paper considers the nonlinear relationship between the three kinds of environmental regulations and GTFP, selects the first-order lag period of GTFP as the explanatory variable, introduces the quadratic term of environmental regulation, and constructs the following model:

$$\ln GTFP_{i,t} = \alpha_0 + \alpha_1 \ln GTFP_{i,t-1} + \alpha_2 \ln ER_{i,t} + \alpha_3 \ln ER_{i,t}^2 + \beta X_{i,t} + V_{i,t} + \varepsilon_{i,t} \tag{18}$$

Where $GTFP_{i,t}$ is the GTFP of the *i*th industry in the year t, $GTFP_{i,t-1}$ indicates the first-order lag of GTFP. $ER_{i,t}$ is the environmental regulation intensity, $ER_{i,t}^2$ is the quadratic value of environmental regulation. $X_{i,t}$ is the other factor affecting the industrial GTFP. $V_{i,t}$ represents the individual effect, and $\varepsilon_{i,t}$ is a random disturbance. The control variable $X_{i,t}$ can be expressed as:

$$X_{i,t} = \gamma_1 \ln Size_{i,t} + \gamma_2 \ln OS_{i,t} + \gamma_3 \ln RCP_{i,t} + \gamma_4 \ln LP_{i,t} + \gamma_5 \ln EP_{i,t} \tag{19}$$

Where $Size_{i,t}$ is the relative scale of the industry. $OS_{i,t}$ is the ownership structure. $RCP_{i,t}$ is the gross profit rate, indicating the profitability of the industry. $LP_{i,t}$ is labor productivity. $EP_{i,t}$ is the energy production efficiency.

Table 4 is a descriptive statistical analysis of the variables in the regression analysis. All data are from the China Statistical Yearbook, China Industry Statistical Yearbook, China Energy Statistical Yearbook, China Statistical Yearbook on Environment, China National Accreditation Service for Conformity Assessment and National Bureau of Statistics.

Table 4 Descriptive statistical analysis of variables

Var.	Obs	Min	Max	Mean	Std.Dev	Index definition
GTFP	444	0.56	3.42	1.23	1.23	Based on Super-EBM and GML index calculation
ER_{MCR}	444	0.01	214.25	21.56	28.55	The intensity of MCR: wastewater and waste gas treatment costs / industrial sales output value
ER_{MIR}	444	5.07	45.84	12.32	5.21	The intensity of MIR: energy costs / energy consumption
ER_{VCR}	408	0.01	47.73	8.50	9.26	The intensity of VCR: EMS quantity / main business income
Size	444	0.00	0.11	0.03	0.02	Industry scale: industrial sales value / total sales value
OS	444	0.00	0.90	0.18	0.18	Ownership structure: industrial state-owned and state-owned holdings paid-in capital/total paid-in capital
RCP	444	0.02	2.90	0.29	0.39	Gross profit margin: (main operating income - main operating cost) / main operating cost
LP	444	9.66	281.15	56.76	44.68	Labor productivity: industrial sales value / average number of employees
EP	444	0.033	25.606	5.526	5.250	Energy production efficiency: industrial sales value / energy consumption

6.2 Strong-PH testing and estimation results

6.2.1 Related tests

Before regression analysis on dynamic panels, the unit root test is firstly performed on the panel data, results are shown in Table 5 . As can be seen in Table 5, AR (2) is greater than 0.05, indicating that there is no second-order autocorrelation in the dynamic panel. The Hansen test P value is greater than 0.05, indicating that the selected tool variable is valid. And the whole test passed the F test.

Table 5 Result of SYSGMM tests

Var.	ALL MCR	H MCR	M MCR	L MCR	A MIR	H MIR	M MIR	L MIR	A VCR	H VCR	M VCR	L VCR
AR (2)	0.170 (0.866)	-0.250 (0.802)	-1.470 (0.142)	0.620 (0.535)	0.290 (0.772)	0.320 (0.746)	-1.150 (0.249)	1.540 (0.123)	1.390 (0.165)	-0.430 (0.664)	-1.010 (0.311)	0.780 (0.437)
Hansen	30.380 (1.000)	0.140 (1.000)	6.250 (1.000)	2.540 (1.000)	33.200 (0.921)	2.740 (1.000)	5.660 (1.000)	0.500 (1.000)	23.890 (1.000)	0.100 (1.000)	5.380 (1.000)	2.380 (1.000)
F	57.570 (0.000)	40.980 (0.000)	24.030 (0.000)	327.630 (0.000)	59.340 (0.000)	28.580 (0.000)	20.270 (0.000)	52.070 (0.000)	44.550 (0.000)	32.970 (0.000)	28.680 (0.000)	47.820 (0.000)

In order to test the regression effect and robustness of SYSGMM, this paper selects static model and SYSGMM model for comparative analysis. The Hausman test is performed on the static panel, if the P value is greater than 0.1, the random effects model is selected. Otherwise, if the P value is less than 0.1, the fixed effects model is selected. Regression results Table 6.

Table 6 Result of Hausman tests

Var.	ALL MCR	H MCR	M MCR	L MCR	A MIR	H MIR	M MIR	L MIR	A VCR	H VCR	M VCR	L VCR
Hausman-P	53.870 (0.000	17.060 (0.030)	7.340 (0.501)	51.64 (0.000)	30.310 (0.000)	15.880 (0.044)	9.580 (0.296)	30.460 (0.000)	44.200 (0.000)	19.880 (0.011)	11.160 (0.193)	23.920 (0.002)

6.2.2 Heterogeneous test of the influence between MCR and GTFP

SYSGMM simulation and the static model of the heterogeneous test of the influence between MCR and GTFP are shown in Table 7.

Table 7 SYSGMM and static model regression: MCR

Variable	ALL_{MCR}		H_{MCR}		M_{MCR}		L_{MCR}	
	FE	SYSGMM	FE	SYSGMM	RE	SYSGMM	FE	SYSGMM
$lnGTFP_{t-1}$		0.785^{***}		0.721^{***}		0.879^{***}		0.830^{***}
		(0.000)		(0.000)		(0.000)		(0.000)
lnER	-2.085	-7.137^{**}	0.231^{***}	0.101^{***}	-0.001	-0.069^{**}	-2.000	-2.918^{***}
	(0.596)	(0.038)	(0.001)	(0.009)	(0.982)	(0.029)	(0.754)	(0.007)
$lnER^2$	1.060	3.569^{**}	-0.448^{**}	-0.344^{***}	0.007	0.107^{**}	1.014	1.460^{***}
	(0.589)	(0.038)	(0.016)	(0.000)	(0.876)	(0.036)	(0.750)	(0.007)
lnSize	-0.124^{***}	0.008	-0.136^{*}	0.072^{***}	-0.006	0.000	-0.207^{***}	0.037^{**}
	(0.000)	(0.394)	(0.099)	(0.009)	(0.804)	(0.996)	(0.003)	(0.034)
lnOS	0.010	-0.005	0.019	0.000	-0.012	-0.007	0.028	-0.001
	(0.427)	(0.405)	(0.641)	(0.993)	(0.250)	(0.303)	(0.163)	(0.911)
lnRCP	0.025	-0.024^{*}	-0.003	0.003	0.038	0.007	0.140	0.012
	(0.264)	(0.073)	(0.938)	(0.894)	(0.147)	(0.429)	(0.286)	(0.700)
lnLP	0.299^{***}	0.058^{**}	0.407^{***}	0.036	0.225^{***}	0.021	0.228^{***}	0.003
	(0.000)	(0.014)	(0.000)	(0.251)	(0.000)	(0.152)	(0.002)	(0.920)
lnEP	0.083^{**}	0.001	-0.028	0.060^{*}	0.091^{***}	-0.004	0.167^{**}	0.006
	(0.037)	(0.913)	(0.782)	(0.096)	(0.001)	(0.718)	(0.050)	(0.806)
_cons	-1.579^{***}	-0.181	-1.857^{***}	0.520^{**}	-0.818^{***}	-0.033	-1.688^{***}	0.182
	(0.000)	(0.208)	(0.000)	(0.038)	(0.000)	(0.595)	(0.001)	(0.405)
Threshold		22.360^{*}		35.319^{***}		15.465		1.397^{**}
		(0.058)		(0.000)		(0.183)		(0.022)
obs	431	395	144	132	168	154	119	109

Note: **, **, *** indicate that the level of significance are 10%, 5% and 1%, respectively.*

As can be seen from Table 7 that, in terms of the MCR, the environmental (ER) coefficient of the whole industry, middle polluted and low polluted industrial sectors are all negative, and the secondary (ER^2) coefficient are positive. It means that there is a "U-shaped" relationship between the MCR and GTFP of all, middle and low polluted industrial sectors. With the increasing of the MCR intensity, GTFP presents a "decreasing-increasing" trend. However, there is an "inverted U-shaped" relationship between the MCR and GTFP of high polluted industrial sectors.

According to the threshold regression[54] and compared with the current environmental regulation intensity, the possible trajectories of the polluted industrial sectors to the MCR are shown in Fig. 8. Fig. 8 shows that, the MCR has obvious heterogeneity effects on different industrial sectors. It is clearly seen that the MCR of the total industry and the low polluted industrial sectors showing a similar trend. The environmental regulation intensity of the both industrial sectors are in the upward stage of the "U" curve, which means that the MCR will enhance the GTFP of both of them. When it comes to the high polluted industrial sectors, its environmental regulation intensity has come to 53.87, which is 53% higher than its threshold value and is in the down phase. This means that, the MCR for the high polluted industrial sectors has exceeded the effective range, more and more the MCR cannot play the role of anticipation. However, the intensity of the MCR on the middle polluted industrial sectors should be strengthened. The GTFP of the middle polluted industrial sectors is 7.784, only reached half of the threshold of 15.465 and is in the down phase. In order to significantly improve GTFP of moderately polluting enterprises, it is necessary to increase the intensity of mandatory environmental regulation so that it can cross the inflection point as soon as possible and enter the upward stage of the U-shaped curve.

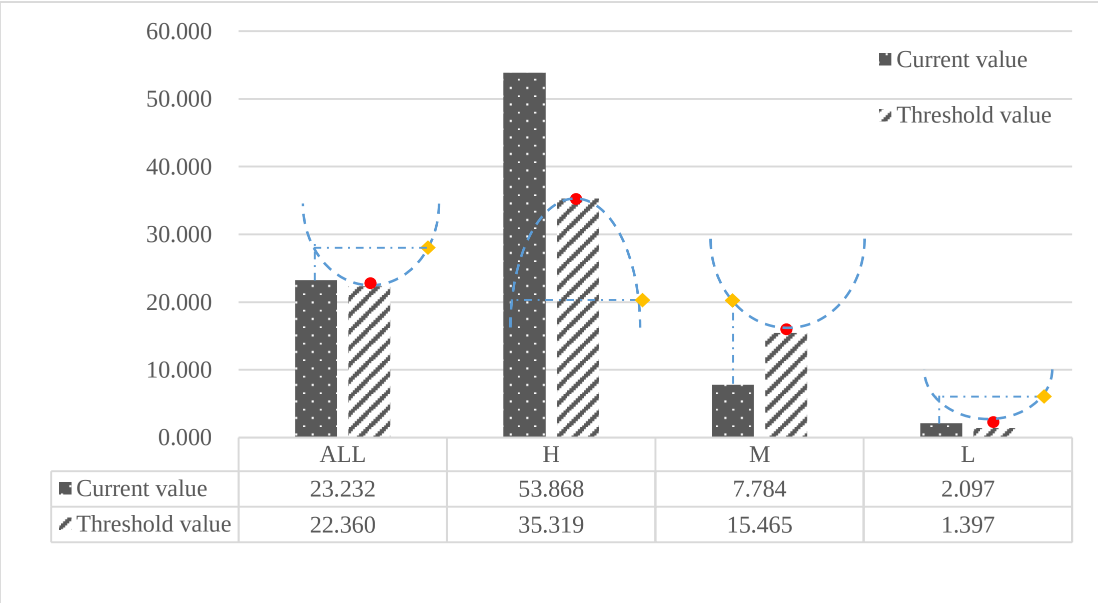

Fig. 8 Possible trajectories of the polluted industrial sectors to the MCR[11]

6.2.3 Heterogeneous test of the influence between MIR and GTFP

SYSGMM simulation and the static model of the heterogeneous test of the influence between MIR and GTFP are shown in Table 8.

[11] Here, the dot icon stands for the threshold values of high (H), middle (M), and low (L) polluted industrial sectors, respectively, and the diamond icon stand for the current value of each sector. What should be noted is that, the "U/∩-shape" line is only a schematic diagram to describe the trend of GTFP, without any actual numerical meaning. The same below.

Table 8 SYSGMM and static model regression: MIR

Variable	ALL_{MIR}		H_{MIR}		M_{MIR}		L_{MIR}	
	FE	SYSGMM	FE	SYSGMM	RE	SYSGMM	FE	SYSGMM
$lnGTFP_{t-1}$		0.782^{***} (0.000)		0.771^{***} (0.000)		0.962^{***} (0.000)		0.591^{***} (0.001)
lnER	-1.292^{*} (0.091)	-1.634^{*} (0.097)	0.341 (0.517)	0.527^{***} (0.004)	1.088^{***} (0.003)	-0.563^{***} (0.001)	-0.130 (0.850)	-6.932^{**} (0.039)
$lnER^{2}$	0.295^{*} (0.076)	0.329^{*} (0.092)	-1.131 (0.360)	-1.402^{***} (0.005)	-2.645^{***} (0.001)	1.424^{***} (0.000)	0.002 (0.315)	0.020^{**} (0.030)
lnSize	-0.091^{***} (0.002)	0.010 (0.437)	-0.240^{***} (0.003)	0.009 (0.340)	0.035 (0.155)	0.005 (0.428)	0.012 (0.849)	0.181 (0.615)
lnOS	0.012 (0.383)	-0.008 (0.280)	0.026 (0.540)	0.000 (0.991)	-0.015 (0.173)	-0.004 (0.498)	0.053^{**} (0.019)	-0.024 (0.299)
lnRCP	0.029 (0.214)	-0.013 (0.367)	0.012 (0.728)	-0.008 (0.615)	0.078^{***} (0.005)	0.020^{**} (0.044)	0.358^{***} (0.003)	1.468^{*} (0.100)
lnLP	0.262^{***} (0.000)	0.054^{*} (0.051)	0.346^{***} (0.000)	0.046^{**} (0.025)	0.198^{***} (0.000)	0.016 (0.184)	0.290^{***} (0.000)	0.549^{**} (0.016)
lnEP	0.082^{*} (0.055)	0.013 (0.254)	-0.062 (0.542)	0.051^{*} (0.063)	0.110^{***} (0.000)	-0.002 (0.806)	0.039 (0.665)	-0.800^{*} (0.056)
_cons	-1.512^{***} (0.000)	-0.013^{*} (0.069)	-1.115 (0.174)	0.819^{**} (0.021)	1.008^{*} (0.051)	-0.866^{***} (0.000)	-0.361 (0.796)	16.768^{**} (0.016)
Threshold		13.750^{***} (0.000)		13.003^{***} (0.000)		11.963^{**} (0.030)		13.660^{***} (0.000)
obs	432	396	144	132	168	154	120	110

Note: **, **, *** indicate that the level of significance are 10%, 5% and 1%, respectively.*

Table 8 shows the regression results from the MIR. It can be seen from the table that all of the corresponding variables have passed the 10% significance test. On the other way, the one-item coefficient of the all-, middle- and low polluted industrial sectors are negative, and their quadratic coefficients are positive, which means that there is a “U-shaped” relationship between MIR and the GTFP of these three industries. Similarly, high polluted industrial sectors exhibit an “inverted U-shaped” relationship. Combined with the threshold regression, the visualization results are shown in Fig. 9.

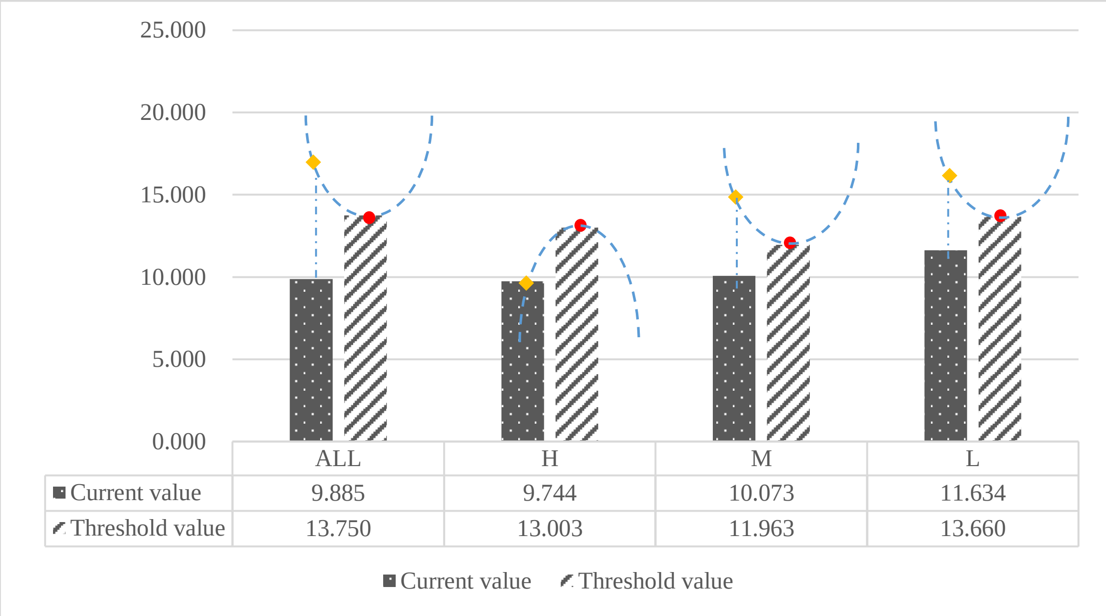

Fig. 9 Possible trajectories of the polluted industrial sectors to the MIR

Fig. 9 shows that, GTFPs of all sectors have not crossed the threshold yet, indicating that there is still room for improvement in the MIR. Among the results, the GTFP of heavy polluted industrial sectors is in a rising stage and the value is likely to reach the threshold of 13.003. While the other three results perform a completely different condition. The whole industry, middle and low polluted industrial sectors are in a declining stage, they need much more MIR measurements to make their GTFPs cross the inflection point and enter the rising period as soon as possible.

6.2.4 Heterogeneous test of the influence between VCR and GTFP

SYSGMM simulation and the static model of the heterogeneous test of the influence between VCR and GTFP are shown in Table 9.

Table 9 SYSGMM and static model regression: VCR

Variable	ALL_{VCR}		H_{VCR}		M_{VCR}		L_{VCR}	
	FE	SYSGMM	FE	SYSGMM	RE	SYSGMM	FE	SYSGMM
$lnGTFP_{t-1}$		0.716^{***}		1.004^{*}		0.863^{***}		0.846^{***}
		(0.000)		(0.080)		(0.000)		(0.000)
lnER	-0.078	-1.319^{*}	-0.040^{**}	-0.193	-0.226	-0.411^{***}	0.759	-4.034^{***}
	(0.847)	(0.063)	(0.018)	(0.261)	(0.321)	(0.007)	(0.972)	(0.000)
$lnER^{2}$	0.020	0.661^{*}	0.013	0.347	0.098	0.208^{***}	-0.320	2.020^{***}
	(0.919)	(0.064)	(0.486)	(0.188)	(0.385)	(0.006)	(0.561)	(0.000)
lnSize	-0.150^{***}	0.019^{**}	-0.248^{***}	0.304	-0.035	0.017	--0.072	0.043^{**}
	(0.000)	(0.029)	(0.002)	(0.324)	(0.156)	(0.197)	(0.353)	(0.044)
lnOS	0.013	-0.004	0.122^{**}	0.478	-0.017^{*}	-0.015	0.022	0.013
	(0.296)	(0.727)	(0.012)	(0.111)	(0.095)	(0.159)	(0.320)	(0.399)
lnRCP	0.042^{*}	-0.012	0.026	0.458	0.020	0.025	0.424^{***}	0.034
	(0.062)	(0.111)	(0.414)	(0.243)	(0.455)	(0.127)	(0.007)	(0.401)
lnLP	0.204^{***}	0.062^{***}	0.183^{**}	-0.142	0.212^{***}	0.031^{**}	0.135^{*}	-0.033
	(0.000)	(0.004)	(0.016)	(0.796)	(0.000)	(0.024)	(0.054)	(0.294)
lnEP	0.138^{***}	0.001	0.223^{**}	0.273	0.099^{***}	0.014	0.113	0.028
	(0.001)	(0.912)	(0.020)	(0.525)	(0.000)	(0.401)	(0.264)	(0.318)
_cons	-1.271	-0.130	-1.279^{***}	3.338	-0.897^{***}	-0.040	-0.320	0.355^{*}
	(0.000)	(0.143)	(0.001)	(0.384)	(0.000)	(0.490)	(0.561)	(0.091)
Threshold		3.855^{***}		4.404^{***}		5.313^{***}		1.564^{***}
		(0.000)		(0.003)		(0.006)		(0.010)
obs	396	363	120	110	168	154	108	99

Note: **, **, *** indicate that the level of significance are 10%, 5% and 1%, respectively.*

As mentioned above, there is a "U-shaped" relationship between GTFP and the VCR regulation for all industries. It should be noted that all the industries have passed the significant test, except the high polluted one, which indicated that the impact of the VCR on high polluted industrial sectors has not yet appeared. Probably because that most of high polluted industrial sectors are far from the public eyes, and the scale of the industry is large, so that weaker the VCR intensity does not have much impact on the industry. Compare the threshold regression results with the current values, the possible trajectories of the polluted industrial sectors to the VCR are shown in Fig. 10.

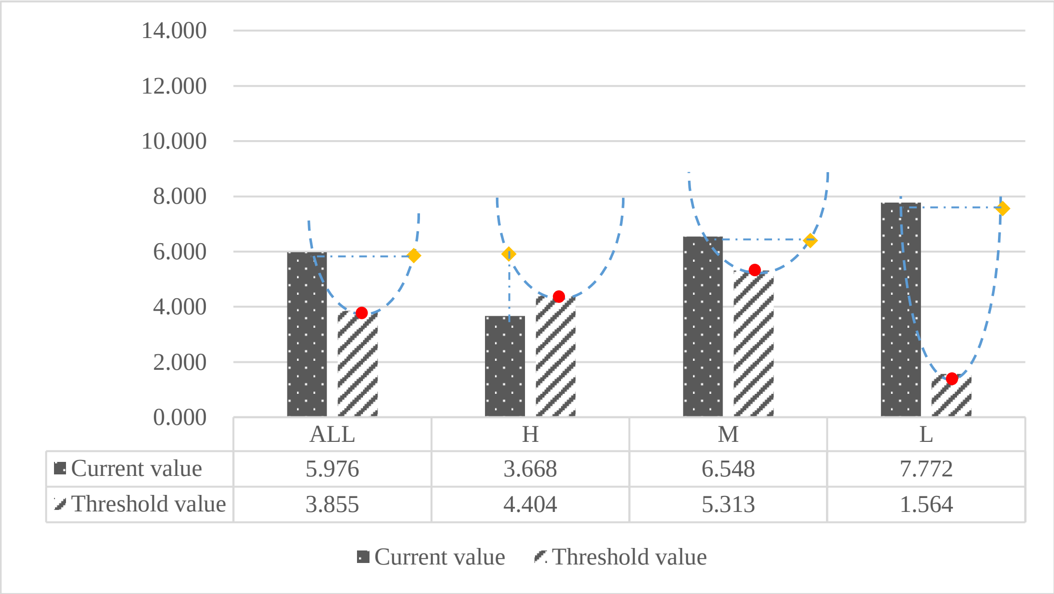

Fig. 10 Possible trajectories of the polluted industrial sectors to the VCR

As can be seen from the Fig. **10** that, the all the target industrial sectors have crossed the turning point, except high polluted industrial sectors. Firstly, high polluted industrial sectors has not crossed the inflection point yet, indicating that the current VCR intensity on high polluted industrial sectors is still weak and should be appropriately upgraded. The current value of middle polluted industrial sectors is 6.548, which has just crossed the threshold of 5.313. it is benefit for the improvement of its GTFP if more and more voluntary participation from the public can be added. The current value of the low polluted industrial sectors is 7.772, which has far exceeded the threshold of 1.564. This can be attributed to the composition of low polluted industrial sectors. It is obviously that low polluted industrial sectors such as tobacco manufacturing and furniture manufacturing are concerned by more social organizations and the public. However, as the environmental regulation is very high in low polluted industrial sectors, it is worth noting that excessive regulatory intensity may lead to high operating costs and burden this industry.

6.2.5 Conclusions for heterogeneous tests

The main results of the heterogeneous tests of three kinds of polluted industries are summarized in Table 10.

Table 10 Summary of the heterogeneous tests

Industrial sectors	Environmental regulation	Trend	Cross the point or not	Measurement
All	MCR		Crossed	Strengthen
	MIR		Non-Crossed	Strengthen
	VCR		Crossed	Strengthen
High	MCR		Crossed	Loosen
	MIR		Non-Crossed	Strengthen
	VCR		Non-Crossed	Strengthen
Middle	MCR		Non-Crossed	Strengthen
	MIR		Non-Crossed	Strengthen
	VCR		Crossed	Strengthen
Low	MCR		Crossed	Keep
	MIR		Non-Crossed	Strengthen
	VCR		Crossed	Keep

Overall, the relationship between different types of environmental regulations and the GTFP of China's polluted industries shows strong heterogeneity. Among all environmental regulations, the MIR which has not crossed the inflection point needs to be paid more attention. From the perspective of industrial sectors,

Heavy polluted industrial sectors: GTFP of high polluted industrial sectors are the highest in the MCR due to the pressure from laws, regulations and policies for a long time, and the MCR has entered the downlink phase which needs appropriate policy relaxation. This is also one of the results of "low-hanging fruits" policy. As the value of the MIR and VCR have not crossed the inflection point, the intensity of MIR and VCR in heavy polluted industrial sectors need to be strengthened.

Middle polluted industrial sectors: Middle polluted industrial sectors should receive enough attention. It is the only one whose GTFP has a lot of room for improvement, three kinds of environmental regulation measurements can be strengthened. For one thing, the MCR and MIR have not crossed the inflection point, for another, although the VCR has crossed the inflection points, the value of GTFP only 1.2 higher than the value threshold, so that, appropriate increase in the VCR will not bring too much pressure on middle polluted industrial sectors.

Low polluted industrial sectors: The intensity of MCR and VCR for low polluted industrial sectors have crossed the inflection point, so it should focus on the MIR. However, although we have to give more attention on the MIR in low polluted industrial sectors, we have to also consider the costs and loss of the industries. It is worth noting that excessive regulatory intensity may lead to high operating costs and burden this industry.

7. Policy suggestions and future work

China faces the dual challenges of economic increasing upward pressure and the continuous deterioration of the environment. In recent years, the state has made remarkable achievements in vigorously rectifying heavy polluted industries with high pollution intensity and large pollution emissions. However, these "low-hanging fruits" that can get good results in short time will be picked up. To solve overcapacity and waste of resources and enhance the core competitive advantage of the polluted industries, the most important task is to adjust the environmental regulations that will guide and assist the polluted industries to improve their GTFP.

This paper tests the heterogeneous effects of strong-PH of China's polluted industries Firstly, the pollution index of 37 industries from 2003 to 2015 are calculated, after that 37 industries are subdivided into high-middle-low polluted industrial sectors. Secondly, the heterogeneous tests of the three kinds of environmental regulations (MCR, MIR, VCR) and the different polluted industrial sectors are given: a) The regulation of the MCR and MIR have a significant impact on the industrial GTFP, verifying the strong-PH. The VCR has no significant impact on heavily polluted industrial sector. b) The same environmental regulation type has different effects on the three industrial sectors, showing obvious industrial heterogeneity. c) The effects of different environmental regulations on the same industrial sector are also different. It is necessary to consider synergies and constraints in the process of setting the environment regulation. d) Middle polluted industrial sectors have a huge room of emission reduction.

Based on the results above, a better understanding and some reasonable perspectives of “low-fruits-first-pick” dilemma are represented:

Transfer of regulatory focus to middle polluted industry. The research results show that China's current environmental achievements are mainly due to the effective implementation of the "low-hanging fruits first pick" environmental policy for high polluted industrial sectors. Nowadays, the middle polluted industrial sectors, which has the same high pollution intensity with high polluted industrial sectors, should be paid enough attention as these low-hanging fruits are going to be picked up. Given the current environmental regulation intensity of this type is still weak, the regulation of the MCR and MIR have not through the turning point, it displays a “U” type with GTFP, and the regulation of the VCR has just crossing the inflection point.

The problem of industrial heterogeneity should be fully considered in environmental regulations. In order to give full play to the potential role of environmental regulation in the industry GTFP, it is necessary to consider the characteristics of industrial heterogeneity in the strong-PH, and to formulate corresponding environmental regulation strategies based on the characteristics of different types of industries. According to the overall situation of the industrial industry, the “one size fits all” style of environmental regulation strategies may not only weaken the willingness of enterprises’ innovate compensation, but also easily lead to regulatory failures and fail to achieve the “win-win” goal of environment and economy.

Three types of environmental regulation are coordinated. At present, China's environmental regulation is still relying on the government's macro-control and policy formulation, there is great potential in the market force and public participation. Therefore, it is necessary to take a full account the characteristics of different environmental regulations, learn from each other and jointly promote the environmental regulation structure to achieve an optimal state.

This paper focus on the relationship between different types of environmental regulations and various polluted industries. Although the above analyses have provided some interesting insights, it has a few limitations. For one thing, different indicators may have different and inter-related results between each other. In that case, composite index seems to be more reasonable for detecting the polluted degree of industrial sectors. However, due to the data availability, this paper inevitably has limitations in the selection of data for the VCR. Secondly, the heterogeneous effects of environmental regulations and regional are not mentioned in this research. We agree that the research of environmental regulations and regions may produce more valuable conclusions. These issues will be included in our future research.

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Reference

[1] Li, K., Lin, B., 2017. Economic growth model, structural transformation, and green productivity in China. Appl. Energy 187, 489-500.

[2] Shen, N., Liao, H.L, Deng, R., Wang, Q.W., 2019. Different types of environmental regulations and the heterogeneous influence on the environmental total factor productivity: empirical analysis of China's industry. Journal of Cleaner Production. 211, 171-184.

[3] Wendling, Z.A., Emerson, J.W., Esty, D.C., Levy, M.A., de Sherbinin, A., et al. (2018). 2018 Environmental Performance Index. New Haven, CT: Yale Center for Environmental Law & Policy

[4] Tian P., Lin B.Q.. 2017. Promoting green productivity growth for China's industrial exports: Evidence from a hybrid input-output model. Energy Policy, 111, 394-402.

[5] Mi, Z.F,, Zeng, G., Xin, X.R., Shang, Y.M., Hai, J.J., 2018. The extension of the Porter hypothesis: Can the role of environmental regulation on economic development be affected by other dimensional regulations? Journal of Cleaner Production. 203, 933-942.

[6] NDRC. Notice of the State Council on the approval of the implementation plan and measures for the statistical monitoring and assessment of energy conservation and emission reduction. 2011-12-2
[Available Online: http://www.ndrc.gov.cn/zcfb/zcfbgg/201112/t20111227_452721.html]

[7] NDRC. Notice on Printing and Distributing the Implementation Plan for Energy Saving and Low Carbon Action of Wanjia Enterprises. 2015-12-30
[Available online: http://www.ndrc.gov.cn/zcfb/zcfbgg/201601/t20160107_770722.html]

[8] Liu, Y., Wei, T., 2016. Market and non-market policies for renewable energy diffusion: a unifying framework and empirical evidence from China’s wind power sector. The Energy Journal. 31 (S1), 195-210.

[9] Porter, M.E., 1991. America's green strategy. Scientific American. 264 (4), 193-246.

[10] Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Review of economics and statistics. 79 (4), 610-619.

[11] Rennings, K., 2000. Redefining innovation d eco-innovation research and the contribution from ecological economics. Ecological Economics. 32 (2), 319-332.

[12] Lanoie, P., Patry, M., Lajeunesse, R., 2008. Environmental regulation and productivity: testing the Porter hypothesis. Journal of Productivity Analysis. 30 (2), 121-128.

[13] Dong, Y., Shi, L., 2013. The Porter hypothesis: a literature review on the relationship between eco-innovation and environmental regulation. Acta Ecol. Sin. 33 (3), 809 824. (In Chinese).

[14] Ramanathan, R., He, Q.L., Black, A., Ghobadian, A., Gallear, D., 2016. Environmental regulations, innovation and firm performance: a revisit of the Porter hypothesis. Journal of cleaner production. 155 (2), 79-92.

[15] Lanoie, P., Ambec, S., Cohen, M.A., Elgie, S., 2013. The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? Rev. Environ. Econ. Pol. 7 (1), 2 22.

[16] Ford J.A., Steen, J., Verreynne, M.L., 2014. How environmental regulations affect innovation in the Australian oil and gas industry: going beyond the Porter hypothesis. Journal of Cleaner Production. 84 (1), 204-213.

[17] Yu, W., Chen, Q., 2015. 20 years of Porter hypothesis — A literature review on the relationship among environmental regulation, innovation and competitiveness. Sci. Res. Management. 36 (5), 65-71 (In Chinese).

[18] Gollop,F.M., Roberts,M.J.,1983.Environmental regulations and productivity growth: the case of fossil-fuelled electric power generation. J.Polit.Econ.91, 654–674.

[19] Gray,W.B.,Shadbegian,R.. 1993. Pollution abatement costs, regulation, and plant-level productivity. NBER Working Paper no.4994, January.

[20] Gray,W.B.,Shadbegian,R..2003. Plant vintage, technology and environmental regulation. Journal of Environ Econ. Management, 46, 384–402.

[21] Berman, E.. 2001. Environmental regulation and productivity: evidence from oil refineries. Review of economics and statistics. 83 (3), 498-510.

[22] Alpay, E., Buccola, S., Kerkvliet, J., 2002. Productivity growth and environmental regulation in Mexican and U.S. food manufacturing. American journal of agricultural economics. 84 (4), 887-901.

[23] Rennings, K., Rammer,C.. 2010. The impact of regulation-driven environmental innovation on innovation success and firm performance. ZEW Discussion Paper no. 10-065.

[24] Lanoie, P., Laurent-Lucchetti,J., Johnstone,N., Ambec,S.. 2011. Environmental policy, innovation and performance: new insights on the Porter Hypothesis. J. Econ. Manag. Strategy, 20, 803–842.

[25] Li, B., Peng, X., Ming-ke, O., 2013. Environmental regulation green total factor productivity and the transformation of China s industrial development mode analysis based on data of China s 36 industries. China Industrial Economics. 4: 56-68. (in Chinese)

[26] Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: empirical evidence on the Porter hypothesis from European manufacturing sectors. Energy policy. 83 (35), 288-300.

[27] Ferjani, A., 2011. Environmental regulation and productivity: a data envelopment analysis for Swiss dairy farms. Agricultural economics review. 12 (1), 44-55.

[28] Li, L., Tao, F., 2012. Selection of optimal environmental regulation intensity for Chinese manufacturing industry based on the green TFP perspective. China Industrial Economics. 5, 70-82. (in Chinese)

[29] He, Y.M., Luo, Q., 2018. Environmental regulation, technological innovation and industrial total factor productivity of China—reexamination of the “strong Porter hypothesis”. Soft Sci. 32 (04), 20-25 (In Chinese).

[30] Wang, Y., Shen, N., 2016. Environmental regulation and environmental productivity: the case of China. Renew. Sustain. Energy Rev. 62, 758-766.

[31] Wang, J., Liu, B., 2014. Environmental regulation and enterprise's TFP: an empirical analysis based on China's industrial enterprises data. Chin. Ind. Econ. 3, 44-56 (In Chinese).

[32] Yuan, B., Ren, S., Chen, X., 2017. Can environmental regulation promote the coordinated development of economy and environment in China's manufacturing industry? A panel data analysis of 28 sub-sectors. J. Clean. Prod. 149, 11-24.

[33] Meng, B., Liu, Y., Robbie, A., Zhou, M.F., Klaus, H. Xue, J.J., Glen, P. Gao, Y.N., 2018. More than half of China’s CO_2 emissions are from micro, small and medium-sized enterprises. Applied energy. 230, 712-725.

[34] Liu, C.J., Zhao, X.M., 2017. Does strong porter hypothesis have industrial heterogeneity?—The perspective from segmentation of industrial carbon intensity. China Population Resources and Environment. 27 (6), 1-9.

[35] Ruhl, J.B., 1999. The Co-Evolution of Sustainable Development and Environmental Justice: Cooperation, Then

Competition, Then Conflict. Duke Environmental Law and Policy Forum. 9 (2), 161-186.

[36] López-Gamero, M.D., Molina-Azorín, J.F., Claver-Cortés, E., 2010. The potential of environmental regulation to change managerial perception, environmental management, competitiveness and financial performance. Journal of Cleaner Production. 18 (10-11), 963-974

[37] Kathuria, V., Sterner, T., 2006. Monitoring and enforcement: Is two-tier regulation robust? — A case study of Ankleshwar, India. Ecological Economics. 57 (3), 477-493.

[38] Pargal, S., Wheeler, D., 1996. Informal Regulation of Industrial Pollution in Developing Countries: Evidence from Indonesia. Journal of Political Economy. 104 (6), 1314-1327.

[39] Lim, S., Prakash, A., 2014. Voluntary Regulations and Innovation: The Case of ISO 14001. Public Administration Review. 74 (2), 233-244.

[40] Zhao, X., Liu, C.J., Yang, M., 2018. The effects of environmental regulation on China's total factor productivity: An empirical study of carbon-intensive industries. Journal of Cleaner Production. 179, 325-334.

[41] Ma, H.Y., Oxley, L., Gibson, J., Kim, B., 2008. China's energy economy: technical change, factor demand and interfactor/interfuel substitution. Energy Economics. 30 (5), 2167-2183.

[42] Wang, B.B., Qi, S.Z., 2016. The effect of market-oriented and command-and-control policy tools on emissions reduction innovation——an empirical analysis based on China's industrial patents data. China Industrial Economics. 6, 91-108. (In Chinese).

[43] Wagner, M., 2007. On the relationship between environmental management, environmental innovation and patenting: Evidence from German manufacturing firms. Research Policy. 36 (10), 1587-1602.

[44] Ahuja, K.G., 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. The Academy of Management Journal. 45 (6), 1183-1194.

[45] Shu, C.L., Zhou, K., Xiao, Y.Z., Gao, S.X., 2016. How green management influences product innovation in China: the role of institutional benefits. Journal of Business Ethics. 133 (3), 471-485.

[46] Avkiran, N.K., Tone, K., Tsutsui, M., 2008. Bridging radial and non-radial measures of efficiency in. Annals of Operations Research. 164 (1), 127-138.

[47] Tone, K., Tsutsui, M., 2010. An epsilon-based measure of efficiency in DEA — a third pole of technical efficiency. European Journal of Operational Research. 207 (3), 1554-1563.

[48] Jin, P.Z., Peng, C., Song, M.L., 2019. Macroeconomic uncertainty, high-level innovation, and urban green development performance in China. China Economic Review. 55, 1-18.

[49] Pastor, J.T., Lovell, C.A.K., 2005. A global Malmquist productivity index. Economics Letters. 88 (2), 266-271.

[50] Färe, R., Logan, J., 1992. The rate of return regulated version of Farrell efficiency. International Journal of Production Economics. 27 (2), 161-165.

[51] Oh, D.H., 2010. A global Malmquist-Luenberger productivity index. Journal of Productivity Analysis. 34 (3), 183-197.

[52] Qiu, B., Yang, S., 2008. A study on the channels of technology spillovers from FDI and the productivity growth of Chinese manufacturing industry. The Journal of World Economy. 31 (8), 20-31. (In Chinese).

[53] Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data model. Economics Papers. 87 (1), 115-143.

[54] Hansen, E., 2010. Sample splitting and threshold estimation. Econometrica. 68 (3), 575-603.