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The Threshold Effect of Environmental Regulation on Green Technology Innovation Capability: An Empirical Test of Chinese Manufacturing Industries

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Abstract

By constructing panel data on green technology innovation input and output for 28 Chinese manufacturing industries over a 12-year time span from 2003 to 2014, the global slack-based measure directional distance function and the global Malmquist–Luenberger index were used to measure the green technology innovation capability of each industry during the period. The intensity of environmental regulation was used as a threshold when constructing the panel threshold model, to empirically test the non-linear relationship between environmental regulation and the capability for green technological innovation. The results show that: (1) From the perspective of the mechanism of action, environmental regulation has two effects on green technology innovation in two different directions: *innovation offset* and *compliance cost*. There is also an asymmetric effect between innovation input and technological progress. (2) As indicated by analysis based on the GML index, there is an inverted U-shaped relationship between environmental regulation and green innovation capability. As the intensity of environmental regulation grows from medium to high, the direction of environmental regulation's effect on green innovation changes from positive to negative. (3) As shown by index decomposition, the relationship between environmental regulation and the green technology progress index is a significantly inverted N-shaped relationship. (4) Comparative analysis shows that environmental regulation's promotion of green technology innovation is strongest when regulation intensity is in the medium range. Therefore, improving the green technology innovation capability of Chinese manufacturing would be helped by promoting environmental regulation reform, rationally formulating the regulatory intensity, and optimizing the quality of environmental regulation.

Keywords: environmental regulation, green technology innovation capability, manufacturing industry, global Malmquist-Luenberger index

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INTRODUCTION

Sustainable development of the manufacturing industry is one of the main driving sources for the Chinese economy's rapid growth during the past three decades. However, due to the extensive development model and the fact that China has been at the tail end of the international industrial chain for a long time, its manufacturing industry has also exacerbated the environmental burden and caused shortages of resources while promoting economic growth. According to statistics, the total energy consumption of the manufacturing industry in 2014 reached 2.5 billion tons of standard coal, accounting for about 59% of total social energy consumption, and discharged manufacturing wastewater amounted to 15.4 billion tons, taking up about 75% of industrial wastewater discharge. China has become a big resource consumption power, and has gradually entered the stage of continuous ecological resource shortage and complex environmental pollution. These increasingly serious resource and environmental problems are realistic dilemmas that China must face in its continuing industrialization.

According to most research, technological progress is an important tool for relieving environmental resource pressures, and ensuring sustainable development. However, Foray and Grübler (1996) argued that technological advances could increase pollution, but were also an important tool for solving environmental problems and a critical way of achieving sustainable development (Jaffe et al. 2003). On the basis of Hick's ideas (1932), Braun and Wield (1996) proposed the concept of green technology. However, as discovered by Jänicke and Jacob (2004), green

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technological progress is highly dependent on government intervention: it is policy-driven.

Continued industrialization is a development path that China will need to maintain for a long period of time into the future. Manufacturing is not only an important part of industry, but also has great influence on China's resource consumption and environmental pollution. According to the Porter Hypothesis and its supporters' ideas, favorable environmental regulation policies can inspire innovation (Porter and Van der Linde 1995). If policy tools to promote green technology innovation in the manufacturing industry while enhancing environmental protection can be found, feasible paths can be explored for the coordinated development of continuing industrialization, resources, and environment. For this reason, this paper probes the impact of environmental regulation on green technology innovation capability in Chinese manufacturing, and explores the relationship between environmental regulation and technology innovation capability, in hope of providing a research basis for the formulation of relevant environmental policies.

LITERATURE REVIEW

The impact of environmental regulation on technological innovation is a topic of great scholarly concern. There are opposing views on the relationship between the two, which we may call the *crowding out* effect and the *innovation offset* effect.

In the *crowding out* viewpoint, which ignores the discussion of long-term sustainability, enterprises will usually be forced to devote a portion of their investment to pollution prevention and emission reduction in order to abide by environmental policies, which do not realize incremental value in financial accounting. Increased investment in environmental technology will inhibit production (Ambec et al. 2013), which may lead to a direct increase in production costs caused by emission reduction or higher input prices due to the impact of regulation (Barbera and McConnell 1990), thereby reducing the capital used by enterprise innovation. Hence, technology innovation is crowded out (Popp and Newell 2012).

The *innovation offset* viewpoint is mainly based on three explanations of the Porter hypothesis: (1) According to the "weak" version of the Porter hypothesis, all enterprises seek to maximize profit. Environmental regulation is an extra environmental restraint, like financial restraints; thus companies will usually seek effective cost-saving methods to comply with new laws and regulations. According to Jaffe and Palmer (1997), although enterprises will surely increase total capital invested in innovation, they will try to lower compliance costs through selective innovation investment. (2) Based on the "strong" version of the Porter hypothesis, environmental policy may encourage enterprises to reconsider production processes rather than enabling them to be fully operated. Therefore, improving cost savings during production is sufficient to strengthen competitiveness. In other words, the increase in innovative capital investment will produce additional profits, exceeding compliance costs. (3) As argued by the "narrow" version of the Porter hypothesis, environmental regulation policies that focus on results rather than process are more likely to increase innovation (Jaffe and Palmer, 1997). Among these, environmental policy instruments that address market failures through price signals have a more significant effect than other kinds of policies. These three perspectives lead to the conclusion that in a well-designed regulatory environment, enterprises can achieve better financial performance and gain the same environmental benefits by making full use of regulatory policies to increase their investment in technological innovation (Gouldson et al. 2009).

In studying regulation intensity, foreign experience shows that stricter environmental regulation has a significant effect on fostering green technology. At the micro level, the strictness of policies has a significant impact on enterprises making decisions on whether or not to be involved in environmental R&D (Arimura et al. 2007, Johnstone and Labonne 2006, Lanoie et al. 2011, Yang et al. 2012). At the industry level, as indicated by Jaffe and Palmer (1997) and Hamamoto (2006), stricter laws and regulations have a positive impact on total R&D expenditure. However, as shown by Kneller and Manderson's (2012) study of the British manufacturing industry, the strictness of environmental regulation is positively correlated with environmental R&D expenditure, but not significantly related to total R&D expenditure. On the macro- and trans-national scales, the significant relationship between stricter environmental regulation and green technology innovation can also be validated (Lanjouw and Mody 1996, Popp 2006).

To sum up, environmental regulation has two mechanisms of function on green technology innovation. The *innovation offset effect* is when implementation of environmental regulation stimulates enterprises to innovate and upgrade production and environmental protection technologies, which can partially or completely offset the costs of implementing environmental regulation and thereby improve enterprises' green technology innovation capabilities. The compliance effect is when environmental regulation increases enterprises' costs for pollution control, which may exert a crowding out effect on the R&D investment made by enterprises. This is not conducive to innovating environmental protection technology or improving environmental governance, and will adversely affect green technology innovation capability in the long run.

At the same time, although environmental regulation has an adverse effect on investment in green technology innovation, there is also an asymmetric effect between innovation input and technological progress, and there is even a Solow paradox phenomenon in R&D investment (Li et al. 2017). As shown by Fernandes (2008), there is no inconsistency between R&D investment and technological progress (Fernandes 2008). As indicated by Zhang (2014), with greater R&D investment growth in China's high-tech industry productivity is gradually declining, and the impact of R&D stock on total-factor productivity growth is first weakened and then strengthened (Zhang 2014). This shows that environmental regulation has both positive and negative effects on green technology innovation. Meanwhile, there is also an asymmetric effect between innovation input and technological progress, which indicates that environmental regulation may have a threshold effect on improving green technology innovation capability. To further understand the relationship between environmental regulation and green technology innovation capability, this paper will carry out an empirical test based on data from Chinese manufacturing.

GREEN TECHNOLOGY INNOVATION CAPABILITY OF CHINESE MANUFACTURING

Methods of Measurement

In recent years, many scholars have used data envelopment analysis (DEA) to explore relevant industry problems such as industrial capacity utilization rates, carbon productivity, energy efficiency (Vaninsky 2006), green (environmental) development performance (Chen and Golley 2014), and so forth, based on an underlying assumption of generalized homogeneous decision-making units. Based on the relaxed DEA model proposed by Tone (2001), undesirable output was included in our analytical framework to construct an SBM model of green technology innovation, as follows:

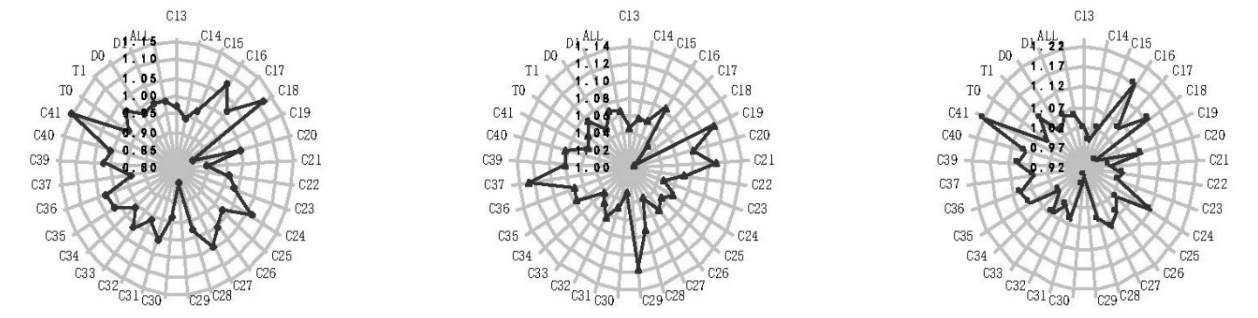
$$\rho^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{i0}}}{\frac{1}{n+k}\left(\sum_{r=1}^{n}\frac{\bar{y}_r}{y_{r0}}+\sum_{l=1}^{k}\frac{\bar{b}_l}{b_{l0}}\right)}$$

$$s.t.\begin{cases} \bar{x} \geq \sum_{j=1,\neq 0}^{J} \lambda_j x_j\,, \\ \bar{y} \geq \sum_{j=1,\neq 0}^{J} \lambda_j y_j\,, \\ \bar{b} \geq \sum_{j=1,\neq 0}^{J} \lambda_j b_j\,, \\ \bar{x} \geq x_0, \bar{y} \leq y_0, \bar{b} \geq b_0, \bar{y} \geq y_0, \lambda_j \geq 0. \end{cases} \quad (1)$$

where $\bar{x}, \bar{y}$, and $\bar{b}$ respectively denote the loose quantities of input, desirable output, and undesirable output. R&D capital stock and R&D personnel were selected as the capital input and labor input, respectively; sales revenue from new products and commercial levels of innovative products were used as the desirable outputs; the undesirable output includes energy consumption and amounts of industrial solid wastes, SO_2 discharged, and industrial wastewater discharged per unit of industrial added value. Data was extracted from the 2004–2015 China Statistical Yearbook on Science and Technology and processed with the trend method and proportional calculation method proposed by Liu et al. (2017). In Equation (1), λ_j is the weight vector, and if its sum is 1, it means the variable returns to scale (VRS); otherwise it means the constant returns to scale (CRS).

The total factor productivity of technology innovation not only reflects the efficiency of technology innovation but also shows the quality of innovation. Therefore, in this study, total factor productivity denotes green technology innovation capability. Based on research done by Oh (2010) and Pastor and Lovell (2005), the directional vector was set as $g = (g_y, g_b), g \in R_+^n \times R_+^k$. The global directional distance function can be expressed as $\vec{D}^G(x, y, b; g_y, g_b) = \max\{\beta | y + \beta g_y, b - \beta g_b) \in P^G(x)\}$. The model for measuring the green technology innovation capability of Chinese manufacturing was constructed as follows:

$$GML_t^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + \vec{D}^G(x^t, y^t, b^t; g_y^t, g_b^t)}{1 + \vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1}; g_y^{t+1}, g_b^{t+1})} \quad (2)$$



Technological efficiency change index Technological change index green innovation GML index

Fig. 1. Map of OMU Pond I and sampling station (Anonymous 1975)

According to the method proposed by Chung, Färe, and Grosskopf (1997), the global Malmquist–Luenberger (GML) index was further decomposed into efficiency change and technological change:

$$GML_t^{t+1} = \frac{1+\vec{D}^G(x^t, y^t, b^t; g_y^t, g_b^t)}{1+\vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1}; g_y^{t+1}, g_b^{t+1})} \times \frac{\dfrac{\left[1+\vec{D}^G\left(x^t, y^t, b^t; g_y^t, g_b^t\right)\right]}{\left[1+\vec{D}^t\left(x^t, y^t, b^t; g_y^t, g_b^t\right)\right]}}{\dfrac{\left[1+\vec{D}^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g_y^{t+1}, g_b^{t+1}\right)\right]}{\left[1+\vec{D}^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g_y^{t+1}, g_b^{t+1}\right)\right]}} = GEE_t^{t+1} \times GTE_t^{t+1} \quad (3)$$

Herein, GEE_t^{t+1} and GTE_t^{t+1} greater (smaller) than 1 denote improved (deteriorated) efficiency and technological progress (retrogress), respectively.

Analysis of Industry Differences

The overall situation

From 2003 to 2004, the mean value of the green technology innovation GML index in Chinese manufacturing increased by 4.96%, and the variation trend (as shown in **Figs. 1a–c**) has obvious periodical characteristics: the growth rate declined from 2003 to 2008 and moved upward from 2008 to 2014. This shows that the green technology innovation capability of Chinese manufacturing is improving overall, and since the transition of China's development mode in 2008, the green technology innovation capability of its manufacturing industry has been further improved. As indicated by the decomposition index, the growth of the green technology innovation GML index mainly comes from technological progress, indicating technological progress is the main driving force in improving green technology innovation. Moreover, the mean value of the technological progress index is 1.065, but it is declining in overall volatility. This is probably because technological progress in Chinese manufacturing primarily occurs through the introduction of new technologies, but with the narrowing of the technology gap, this kind of technological progress lacking originality is becoming unsustainable, barring new technological innovations. Additionally, the mean value of technical efficiency change is 0.986, restricting the improvement of green technology innovation capability; but the overall trend is rising in volatility. Total factor productivity and green innovation capability are the keys to greening economic growth.

Although these results show that the green technology innovation GML index in Chinese manufacturing is growing at an average annual rate of 4.96%, it clearly has not achieved a growth rate equal to that of GDP or industrial added value. This indicates that, on the one hand, past Chinese manufacturing has been dominated by extensive development; on the other hand, it also shows that the green innovation capability of Chinese manufacturing has great growth potential. Meanwhile, the green technology innovation GML index mainly comes from technological progress, indicating that the promotion of technological progress is the key to enhancing green innovation capability.

Industry differences

From the business perspective, the average green technology innovation GML index of the rest 23 industries except food manufacturing, furniture manufacturing, rubber products, plastic products, leather, fur, and feathers (velvet) and its related products industries, is > 1 and the GML index of all the samples is also > 1. This indicates that the green technology innovation capability of Chinese manufacturing is characterized by an upward trend overall. Additionally, as implied by index decomposition, the green technology efficiency variability index of 12 industries is > 1, but the green technology efficiency index of the overall sample is < 1, which indicates that Chinese manufacturing still needs to strengthen its ability to transform scientific and technological achievements. Finally, the green technological progress index of each industry is > 1 and greater than the green technology efficiency variability index, while the green technological progress index of the overall samples is also > 1 as well, implying that technological progress is the main factor promoting the green technology innovation capability of each manufacturing industry.

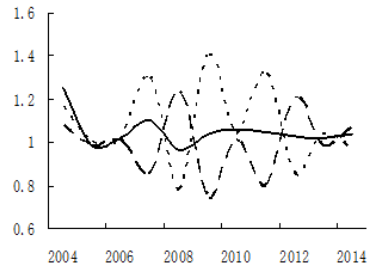
To better analyze the differences between various industries, industries in Chinese manufacturing were divided into two categories. First, we classified industries according to energy consumption and pollution emission. Ten manufacturing industries were listed as polluting industries: agricultural and sideline food processing; food manufacturing; textiles; paper making and paper products; petroleum processing; coking and nuclear fuel processing; chemical and chemical products manufacturing; chemical fiber manufacturing; non-metallic mineral products; and ferrous and non-ferrous metal smelting, rolling, and processing. The remaining industries were listed as clean industries. Second, we classified industries according to technology type. Eight industries were classified as high-tech industries: chemical and chemical products manufacturing; pharmaceutical manufacturing; chemical fiber manufacturing; special equipment manufacturing; transportation equipment manufacturing; electric machinery and equipment manufacturing; communication device, computer, and other electronic equipment manufacturing; and instrument, cultural, and office machinery manufacturing. The remaining 20 industries were classified as medium and low-tech. As indicated in **Figs. 1a–c**, industries in different categories are significantly different from each other when it comes to average GML index, with the green technology innovation GML index of the high-tech industries being highest and that of the polluting industries being the smallest. This reveals the difference caused by industry heterogeneity among different industries in Chinese manufacturing in terms of green technology innovation efficiency. As the main source of economic growth, manufacturing also provides a material basis for social development. Thus, green development of the manufacturing industry directly relates to the green development of the whole society. Our results show that the key to enhancing the green innovation capability of the manufacturing industry is to optimize the industrial structure and speed up supply-side structural reform.

Analysis of the key industries

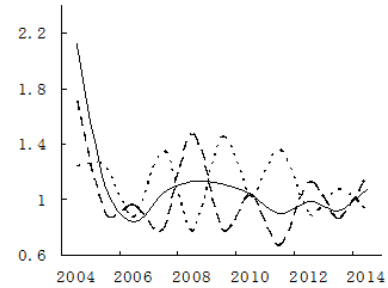
Given the significant differences between different manufacturing industries in terms of green technology innovation capability, five representative key industries were selected for analysis according to government support for industry innovation, foreign investment, business environment, enterprise scale, and industry structure, etc. **Figs. 2a–f** show the dynamic change of the green technology innovation GML index and corresponding decomposition index of all the manufacturing industries (C0); the wood processing and wood, bamboo, rattan, palm, and grass products industries (C20); papermaking and paper products industries (C22); pharmaceutical manufacturing (C27); non-ferrous metal smelting and rolling (C33); and communication device, computer and other electronic equipment manufacturing (C40).

From 2003 to 2014, government funding of large and medium-sized pharmaceutical manufacturing R&D reached an annual average of 8.515 billion yuan, accounting for 1.34% and 2% of their sales revenue and operating expenses, respectively. This proportion is the highest among the 28 manufacturing industries, reflecting the national emphasis on industries oriented towards people's well-being and inspiring the researchers to carry out the study in this field. The mean value of the green technology innovation GML index of the pharmaceutical manufacturing industry (C27) is 1.08 (larger than that of the manufacturing industry overall) and is characterized by a wavelike rise. The mean value of its green technology efficiency index is 1.04, higher than that of the manufacturing industry overall. The mean value of its green technology progress index is 1.04. As shown in **Fig. 2d**, its technological efficiency and technological change increase alternately, and both of them are higher than the averages for the manufacturing industry as a whole.

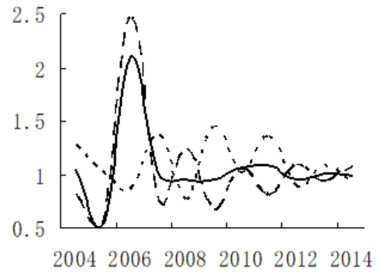
Communication device, computer and other electronic equipment manufacturing (C40) attracts the largest proportion of foreign investment in China. From 2003 to 2014, the annual average foreign fixed-asset investment (including Hong Kong, Macao and Taiwan, and excluding farmers) was 128.567 billion yuan, accounting for 55% of the total amount of fixed-asset investment in China. As shown in Fig**. 2f**, its green technology efficiency index is basically a horizontal line, and its green technology progress index is almost synchronous with its green technology innovation GML index; with a larger fluctuation range, but it is rising as a whole. The mean values of the two indexes are 1.083 and 1.084 respectively, higher than the average. This shows that technologies in this industry are eliminated quickly; it also implies that China's



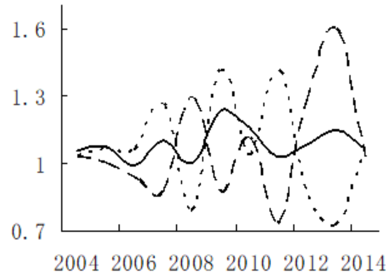
(a) All manufacturing industries (C0)



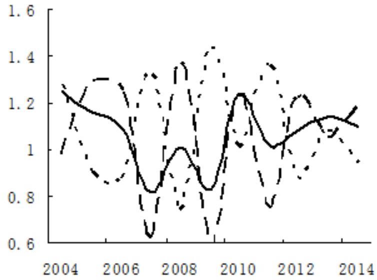
(b) Wood processing and relevant products (C20)



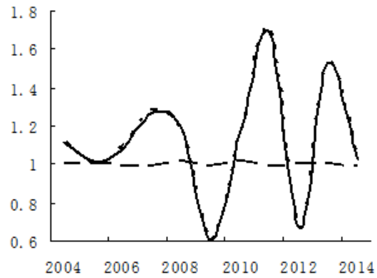
(c) Paper making and paper products (C22)



(d) Pharmaceutical manufacturing (C27)



(e) Non-ferrous metal smelting and rolling (C33)



(f) Communication device, computer and other electronic equipment manufacturing (C40)

Fig. 2. (1)Dynamic diagrams of the green technology innovation GML indexes of all the manufacturing industries and several key manufacturing industries: (**a**) all industries; (**b**) wood processing and related products; (**c**) paper making and paper products; (**d**) pharmaceutical manufacturing; (**e**) non-ferrous metal smelting and rolling; (**f**) communications, computer, and electronics manufacturing. The full line shows the variation of the green technology innovation GML index, the broken line shows that of the green technology efficiency index, and the dotted line reveals that of the green technology progress index

strategy of exchanging the market for technologies has achieved remarkable results in this industry.

The added value of the paper-making and paper products industry (C22) is not high enough, and due to its capacity for environmental damage and the high investment it requires, financing is often discriminated against by the financial industry, especially with the emphasis on environmental protection in various regions. As a consequence, the operating environment of this industry has constantly deteriorated. In terms of index decomposition, although the mean value of the technology progress index is 1.067, slightly higher than that of industry overall, the mean value of the technology efficiency index is only 0.956, making its average GML index lower than that of all industries. As indicated in the dynamic diagram, the industry's GML index is declining, and is consistently > 1 after 2011.

The wood-processing and wood, bamboo, rattan, palm, and grass products industry (C20) is a typically decentralized industry. From 2003 to 2014, the sales value of large and medium-sized enterprises accounted for only 26.79% of the above enterprise, and was declining from an overall perspective. This reflects workshop-style production, and it is also caused by the constant concentration of raw materials in this industry. According to Figure 2b, though the industry's green technology progress showed a wavelike rising trend, the overall decline of its green technology efficiency led to a sharp decline of the GML index.

Enjoying a special position in the Chinese manufacturing industry, non-ferrous metal smelting and rolling (C33) has significantly improving its sales value during recent years due to its unique resource advantage, especially after the implementation of the rare earth export quota policy. It can be seen in **Fig. 2e** that the GML index has significantly improved since 2008.

As the green technology innovation GML indexes and decomposition indexes of the above five manufacturing industries indicate, the green technology innovation capability of industries significantly affected by government support, foreign investment, business environment, enterprise scale, and industry structure is significantly higher or lower than the overall trend. Therefore, in the empirical process of this study, related factors will be incorporated into the control variables.

VERIFICATION OF THE THRESHOLD EFFECT

The Threshold Model

As suggested by currently existing literature, there are two main methods for testing the threshold effect: group testing (Girma et al. 2001) and cross term model testing (Kathuria 2007). Each method has its advantages and disadvantages. The former chooses the cut point to divide the samples into different groups, but it has two shortcomings: there is no objective criterion to divide the samples and it is unable to conduct significance testing for different regression results. By establishing a linear model containing the cross terms, cross term model testing studies the interactions between each variable, but it is difficult to determine the form of the cross terms and the method cannot be used to conduct the significance testing of different regression results. Hansen (1999) creatively proposed a panel data threshold regression model that incorporated the threshold variable into the regression model as an unknown variable, and established a piecewise function to further estimate and verify each threshold and threshold effects. The threshold panel model does not require a given form of the nonlinear equation, and the number of thresholds is internally determined by the number of samples, avoiding the bias caused by subjective division.

According to the Porter hypothesis and its supporters, favorable environmental regulation policies can inspire innovation. It is clear that favorable environmental regulation requires not only action, but also intensity. Considering that exhaust emission and the generation of solid waste are directly related to energy consumption, this paper selected the change rates of energy consumption and wastewater discharge per unit of industrial added value to represent the intensity of environmental regulation. We applied the method proposed by Sun and Wang (2014) to calculate the comprehensive index as the threshold variable, analyzed the threshold effect of environmental regulation on the green technology innovation capability (GML index), and constructed a single-threshold model:

$$\begin{aligned} gie_{i,t} &= \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} \\ &+ \beta_1 er_{i,t} \cdot I(er_{i,t} \leq \gamma_1) + \beta_2 er_{i,t} \cdot I(er_{i,t} > \gamma_1) + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where i denotes industry; t represents time; $gie_{i,t}$ refers to the GML index of Industry i in year t; er denotes environmental regulation; and rd, fdi, be, es and io are government support, foreign investment, business environment, enterprise scale, and industrial structure, respectively. In Equation (4), γ denotes the unknown threshold, $\varepsilon_{i,t}$ is the random disturbance term, and $I(\cdot)$ is the index function, which is equivalent to the following piecewise function:

$$gie_{i,t} = \begin{cases} \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} + er_{i,t}, & er_{i,t} \leq \gamma_1 \\ \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} + er_{i,t}, & er_{i,t} > \gamma_1 \end{cases} \tag{5}$$

Next, based on the test results of the threshold effect, a multi-threshold model was further constructed:

$$\begin{aligned} gie_{i,t} &= \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} \\ &+ \beta_1 er_{i,t} \cdot I(er_{i,t} \leq \gamma_1) + \beta_2 er_{i,t} \cdot I(\gamma_1 < er_{i,t} \leq \gamma_2) \\ &+ \ldots + \beta_n er_{i,t} \cdot I(er_{i,t} > \gamma_n) + \varepsilon_{i,t} \end{aligned} \tag{6}$$

Stationary Test of Data

For this study, the panel data of 28 manufacturing industries in China (excluding waste resources and waste materials recycling, handicrafts, and other manufacturing industries) were selected to estimate the threshold model described above. To improve the stability of the estimated results, stationary tests including the unit root test and cointegration test were carried out using the data involved in the model.

Unit root test

To estimate the validity of the results and avoid spurious regression problems as much as possible, a stationary test of the panel data should be conducted before setting the model and estimating the parameters. In this study, LLC, IPS, ADF–Fisher, and PP–Fisher methods were used for the unit root test. The test results are shown in **Table 1**.

As shown in **Table 1**, in the absence of first-order difference of the variables *rd*, *be*, *io* and *er*, the results of the four unit root test methods are all significant at the 1% confidence level. That is, there is no unit root. However, there are unit roots in the gie, fdi and es sequence. These three variables are significant at the level of 1% after the first-order difference; that is, the original hypothesis is rejected. Thus, the differential sequences of all the sequences of the model are stationary, and all the first-order difference tests do not contain unit roots, and thus have good stationarity.

Table 1. The unit root test results of the panel data

Variable	LLC	IPS	Fisher-ADF	Fisher-PP
gie	–11.261***	–1.213	86.205***	72.160*
△gie	–20.489***	–10.269***	206.165***	238.312***
rd	–37.162***	–12.118***	159.070***	185.827***
△rd	–29.430***	–13.972***	233.258***	372.254***
fdi	–3.798***	0.568	51.867	68.258
△fdi	–12.783***	–7.189***	162.500***	171.255***
be	–7.055***	–3.330***	98.542***	126.483***
△be	–16.866***	–9.216***	194.363***	267.998***
es	–4.727***	–1.734**	69.808	44.002
△es	–10.357***	–5.287***	125.920***	147.406***
io	–14.831***	–8.953***	173.297***	228.408***
△io	–18.957***	–11.378***	234.829***	401.087***
er	–11.044***	–6.631***	141.145***	159.303***
△er	–18.959***	–12.039***	246.936***	352.880***

Notes: ***, ** and * denote that the estimated values are significant at the levels of 1%, 5% and 10% respectively

Table 2. The cointegration test results of the panel data

Test method	Hypotheses Testing	Name of statistics	Statistics (P value)		
Kao Test	H_0: $\rho=1$	ADF	4.765	(0.000)	***
Pedroni Test	H_0: $\rho=1$ H_1:$(\rho_i=\rho)<1$	Panel v–Statistic	7.024	(0.000)	***
		Panel rho–Statistic	7.887	(1.000)	
		Panel PP–Statistic	–12.272	(0.000)	***
		Panel ADF–Statistic	-2.082	(0.019)	**
	H_0: $\rho=1$ H_1:$(\rho_i=\rho)<1$	Group rho–Statistic	9.921	(1.000)	
		Group PP–Statistic	–16.818	(0.000)	***
		Group ADF–Statistic	–1.697	(0.045)	**

Notes: ***, ** and * denote that the estimated values are significant at the levels of 1%, 5% and 10% respectively

Table 3. The threshold effect test

Model	F value	P value	Critical value		
			1%	5%	10%
Single-threshold	12.732***	0.000	9.031	5.018	4.223
Double-threshold	3.575*	0.090	7.740	4.480	3.256
Triple-threshold	2.741	0.140	7.022	5.039	3.903

Notes: (1) Bootstrap times are based on the method applied by Wang et al. (2016)[33] with 100 instances of repeated sampling; (2) ***, ** and * denote that the estimated values are significant, at levels of 1%, 5%, and 10%, respectively

Cointegration test

According to the unit root test results, variables of the model are intergrated of order one. Therefore, it is necessary to conduct a cointegration test of the data to determine whether there is a cointegration relationship between each variable. In this study, the Kao test and Pedroni test were applied to test the panel data. Results are shown in **Table 2**.

As can be seen in **Table 2**, the Kao test results show that the ADF of the panel data is significant, at a confidence level of 1%, indicating that there is a significant cointegration relationship between the variables of the panel data. According to the Pedroni test results, PP and ADF are significant at statistical levels of 1% and 5%, which means the original hypothesis is rejected. The above test results show that the panel data have passed the cointegration test, and there is a significant cointegration relationship between the variables.

Empirical Results

The number of thresholds

In accordance with the principle of the panel threshold model and the original hypotheses, the original hypotheses was tested successively—without threshold value, with one threshold value, and with multiple thresholds—to obtain the F statistic. The P value was gained by the self-sampling method (Bootstrap) (see **Table 3**).

As indicated in **Table 3**, the effects of single-threshold and double-threshold models are significant, with corresponding self-sampling P values of 0.000 and 0.090 respectively, which are significant at 1% and 10% significance levels, respectively. The effect of the triple-threshold model is not significant, and the self-sampling P value is 0.14. Therefore, the following analysis will be carried out based on the double-threshold model.

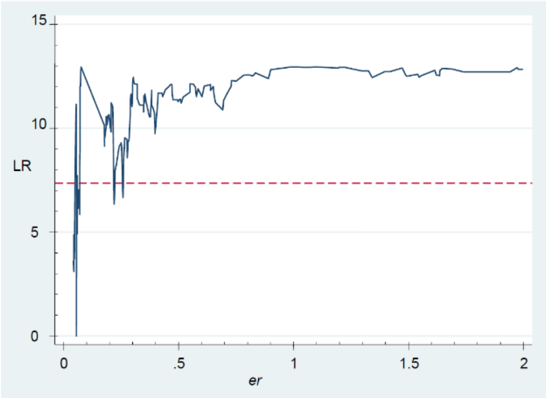


Fig. 3. First estimated threshold value and confidence interval

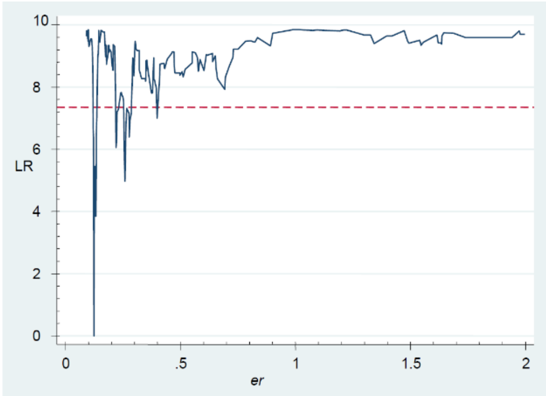


Fig. 4. Second estimated threshold value and confidence interval

Table 4. Results of the estimated threshold values

Testing	Estimated value	95% confidence interval
Threshold value γ_1	0.057	[0.042,0.259]
Threshold value γ_2	0.124	[0.121,0.398]

Threshold value

The LR statistic of least squares was used to identify the threshold value. **Figs. 3** and **4** show the LR functions of the two estimated threshold values.

Table 4 shows the two estimated threshold values and their corresponding 95% confidence intervals. As indicated by **Figs. 2a–f** and **Fig. 3**, the 95% confidence intervals of γ_1 and γ_2 are [0.042,0.259] and [0.121,0.398] respectively, where LR values are both < 7.35 and the critical value is at the 5% significance level, corresponding to the interval formed by γ in the dotted line.

These results indicate that there is a nonlinear relationship between the intensity of environmental regulation and green technology innovation capability. According to the two thresholds, the intensity of environmental regulation on various Chinese manufacturing industries is divided into three intervals:

Table 5. Industries in different threshold intervals

Regulation intensity	Threshold interval	Industry
Low intensity	$er \leq 0.057$	C16, C21, C40, C41
Medium intensity	$0.057 < er \leq 0.124$	C18, C23, C24, C36, C37, C39
Low intensity	$er > 0.124$	C13, C14, C15, C17, C19, C20, C22, C25, C26, C27, C28, C29, C30, C31, C32, C33, C34, C35

Notes: C13,…,C41 denote the industrial codes for each manufacturing industry, which are matched with *Industrial Classification and Codes for National Economic Activities* (GB/T 4754-2002)

low regulation intensity ($er \leq 0.057$), medium regulation intensity ($0.057 < er \leq 0.124$), and high regulation intensity ($er > 0.124$). **Table 5** shows the industries in each interval in 2014.

As shown in **Table 5** (1) There are 4 industries with relatively low regulation intensity: tobacco; furniture manufacturing; communication equipment, computers and other electronic equipment manufacturing; and instrument, cultural, and office machinery manufacturing. (2) There are six industries with medium regulation intensity: textile, garments, shoes and hats manufacturing; printing and recording media reproduction; stationary and sporting goods manufacturing; special equipment manufacturing; transportation equipment manufacturing; and electric machinery and equipment manufacturing. (3) The remaining 18 industries are relatively highly regulated.

Estimated results of the threshold model

The parameters of the double-threshold model were estimated based on the fixed effect. The results are shown in **Table 6**.

As indicated by the estimated results in **Table 6**, the five influencing factors— government support, foreign investment, business environment, enterprise scale, and industry structure—are consistent with the previously observed results. With environmental regulation as the threshold, (1) The estimated results of the threshold effect show that environmental regulation in all three intervals has a significant impact on green innovation capability. In view of the estimation coefficient, there is an inverted U-shaped relationship between environmental regulation and green technology innovation capability. (2) When the regulation intensity of an industry is in the first interval, the estimation coefficient is 10.17, and it is at the significant level of 1%, indicating that improving environmental regulation intensity in this interval can significantly promote green technology innovation capability. (3) When regulation intensity crosses the first interval, the estimation

Table 6. Parameter estimation results of the threshold model

Explained variable: *gie*	Estimated coefficient	Standard deviation	T value
rd	2.274	0.105	1.63
fdi	0.0948***	0.001	3.28
be	–0.597***	0.000	–4.04
es	3.454***	0.005	2.80
io	2.390***	0.000	3.82
er ($er \leq 0.057$)	10.17***	0.009	2.62
er ($0.057 < er \leq 0.124$)	3.056*	0.084	1.78
er ($er > 0.124$)	–2.971*	0.076	–1.74

Notes: ***, ** and * denote that the estimated values are significant at the levels of 1%, 5% and 10% respectively

coefficient becomes 3.056, and is at the significant level of 10%, which indicates that improving environmental regulation intensity in this interval can still promote green technology innovation capability. However, the effect coefficient is obviously lower than that of the first interval. (4) As environmental regulation intensity crosses the second threshold, the estimation coefficient becomes –2.971 and is significant at the level of 10%, implying that enhanced environmental regulation in this interval will suppress green technology innovation capability. This further shows that the impact of environmental regulation on green technology innovation capability is not monotonically increasing or decreasing; there is an inflection point.

There is a non-linear relationship between environmental regulation intensity and green technology innovation capability. When the regulation intensity is in the first and second intervals, increasing it will help promote green technology innovation. In these two intervals, the *innovation offset effect* can clearly exceed than the *compliance cost effect*. Hence, improving environmental regulation intensity at these stages can stimulate enterprise motivation to innovate with green technology, thus significantly enhancing their green innovation capability.

When environmental regulation spans the second threshold value, it is clear that environmental regulation intensity negatively affects green innovation capability. The *compliance cost effect* in this interval can be significantly larger than the *innovation offset effect*. This might be because environmental regulation has increased the costs of pollution control and hindered production, because emission reduction has led to a direct rise in the production costs, or because environmental regulation has increased input price, thereby exerting a crowding-out effect on green technology innovation capability.

DISCUSSION

The Threshold Model Based on Index Decomposition

According to Equation (3), the green technology innovation capability GML index can be decomposed into efficiency change and technological change. To further analyze how environmental regulation influences the green innovation capability of the manufacturing industry, the influences of environmental regulation on the green technology progress index and of technological change of green technology innovation will be discussed below.

Based on Equation (4) and (6), this study constructed two single-threshold models showing the respective impacts of environmental regulation on the green technology progress index and the pure technological efficiency of green technology:

$$\begin{aligned} gte_{i,t} = {} & \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} \\ & + \beta_1 er_{i,t} \cdot I(er_{i,t} \leq \gamma_1) + \beta_2 er_{i,t} \cdot I(er_{i,t} > \gamma_1) + \varepsilon_{i,t} \end{aligned} \tag{7}$$

$$\begin{aligned} gee_{i,t} = {} & \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} \\ & + \beta_1 er_{i,t} \cdot I(er_{i,t} \leq \gamma_1) + \beta_2 er_{i,t} \cdot I(er_{i,t} > \gamma_1) + \varepsilon_{i,t} \end{aligned} \tag{8}$$

Alternatively, based on the testing results of the threshold effect, the following multi-threshold models were established:

$$\begin{aligned} gte_{i,t} = {} & \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} \\ & + \beta_1 er_{i,t} \cdot I(er_{i,t} \leq \gamma_1) + \beta_2 er_{i,t} \cdot I(\gamma_1 < er_{i,t} \leq \gamma_2) \\ & + \ldots + \beta_n er_{i,t} \cdot I(er_{i,t} > \gamma_n) + \varepsilon_{i,t} \end{aligned} \tag{9}$$

$$\begin{aligned} gee_{i,t} = {} & \delta_0 + \alpha_1 rd_{i,t} + \alpha_2 fdi_{i,t} + \alpha_3 be_{i,t} + \alpha_4 es_{i,t} + \alpha_5 io_{i,t} \\ & + \beta_1 er_{i,t} \cdot I(er_{i,t} \leq \gamma_1) + \beta_2 er_{i,t} \cdot I(\gamma_1 < er_{i,t} \leq \gamma_2) \\ & + \ldots + \beta_n er_{i,t} \cdot I(er_{i,t} > \gamma_n) + \varepsilon_{i,t} \end{aligned} \tag{10}$$

In Equations (7) and (9), $gte_{i,t}$ is the green technology progress index of i industry in the year t. In Equations (8) and (10), $gte_{i,t}$ stands for the pure technological efficiency of green technology of i industry in the year t.

The Influences of Environmental Regulation on Green Technological Efficiency and Green Technology Progress

The method described above was used to estimate the threshold models of environmental regulation's effects on the green technology progress index and the

Table 7. The threshold effect test

Explained variables	Model	F value	P value	Critical value 1%	5%	10%
gte	Single-threshold	9.809**	0.020	15.495	8.094	5.883
	Double-threshold	4.597*	0.080	10.341	6.025	4.399
	Triple-threshold	2.318	0.170	6.501	4.685	2.966
gee	Single-threshold	16.879***	0.000	9.241	4.666	3.451
	Double-threshold	5.383**	0.030	6.424	4.383	3.194
	Triple-threshold	5.453*	0.080	10.243	6.370	4.972

Notes: (1) Bootstrap times are based on the method applied by Wang et al. (2016)[33], with repeated sampling applied 100 times. (2) ***, ** and * denote that the estimated values are significant at the levels of 1%, 5% and 10%, respectively

Table 8. Estimated results of the threshold value

Explained variables	Testing	Estimated value	95% confidence interval
gte	Threshold value γ_1	0.045	[0.042,1.997]
	Threshold value γ_2	0.111	[0.087,1.997]
gee	Threshold value γ_1	0.048	[0.042,0.695]
	Threshold value γ_2	0.259	[0.076,1.997]

Table 9. Estimated results of parameters of the threshold model

Explained variable : *gte*	Model (A)	Explained variable: *gee*	Model (B)
rd	–1.164	*rd*	1.992**
	–1.32)		(2.58)
fdi	0.151***	*fdi*	–0.00697
	(7.98)		(–0.42)
be	–0.533***	*be*	0.0763
	(–5.55)		(0.91)
es	1.653**	*es*	3.216***
	(2.06)		(4.59)
io	–0.0858	*io*	1.534***
	(–0.21)		(4.32)
er ($er \leq 0.045$)	–8.128**	*er*($er \leq 0.048$)	11.22***
	(–2.35)		(3.71)
er ($0.045 < er \leq 0.111$)	3.414***	*er* ($0.048 < er \leq 0.259$)	–0.553
	(2.62)		(–0.49)
er($er > 0.111$)	–3.403***	*er* ($er > 0.259$)	0.591
	–2.62)		(0.52)

Notes: ***, ** and * denote that the estimated values are significant at the levels of 1%, 5%, and 10% respectively

pure technological efficiency of green technology, respectively. **Tables 7–9** report the testing results of the threshold effect, the estimated results of the threshold values, and the estimated parameters of the threshold models, respectively.

As shown in **Table 7**, (1) With regard to environmental regulation's effect on green technology progress, the single-threshold and double-threshold models have significant effects, and the corresponding self-sampling P values are 0.020 and 0.080 respectively, which are significant at the levels of 5% and 10%, respectively. However, the triple-threshold model does not have a significant effect, and the self-sampling P value is 0.17. (2) When green technology innovation efficiency is the explained variable, the effects of the single-threshold, double-threshold, and triple-threshold models are significant at the levels of 1%, 5%, and 10%, respectively.

Next, double thresholds will be selected to discuss the above two models.

According to the results shown in **Table 8**, whether the variable used is the green technology progress index or the pure technological efficiency of green technology innovation, the likelihood ratio values of the two estimated threshold values, γ_1 and γ_2, are both smaller than the critical value, at a significance level of 5%.

As shown by the estimated results of the threshold effect in **Table 9**, there are significant differences between environmental regulation's effects on the green technology progress index and the pure technological efficiency of green technology innovation.

In terms of environmental regulation's effect on the green technology progress index as indicated by Model (A): (1) When the regulation intensity of an industry is in the first interval, the estimated coefficient is –8.128

and is significant at the level of 1%. This implies that promoting environmental regulation in this interval significantly restrains the green technology progress index. (2) When regulation intensity crosses the first interval, the estimated coefficient is 3.414 and is significant at the significant level of 1%. This means that improving environmental regulation intensity in this interval can significantly promote the progress of green technology progress. (3) When environmental regulation intensity crosses the second threshold, the estimated coefficient becomes –3.403 and is significant at the level of 1%, indicating that strengthening environmental regulation intensity in this interval will also inhibit green technology progress. These results show that the impact of environmental regulation on the green technology progress index is not simply increasing or decreasing. Instead, there is a significant inverted N-shaped relationship.

In terms of environmental regulation and the pure technological efficiency of green technology innovation, Model (B) indicates: (1) When the regulation intensity of an industry is in the first interval, the estimated coefficient is 11.22 and is significant at the level of 1%, implying that enhancing environmental regulation intensity in this interval can significantly promote the pure technological efficiency of green technology innovation. (2) When the regulation intensity crosses the first interval, the estimated coefficient is –0.553, but t is not statistically significant. (3) As environmental regulation intensity crosses the second threshold, the estimated coefficient is 0.591, which is also statistically insignificant. These results show that when environmental regulation is in the first interval, increasing environmental intensity can significantly improve the pure technological efficiency of green technology innovation. However, after it crosses the first threshold, enhancing environmental regulation intensity does not have an obvious effect on promoting the pure technological efficiency of green technology innovation.

By comparing the estimated threshold results of Models (A) and (B), the following conclusions are reached: first, when environmental regulation intensity is relatively low, the thresholds of the two models are very close to each other and are also close to the threshold values in **Table 6**. In terms of the estimation coefficient, although the coefficient of Model (A) is negative, the estimated value of Model (A) is nonetheless lower than that of Model (B). Therefore, the coefficient of **Table 6** is significantly positive. This result shows that when regulation intensity is comparatively low, the improvement of environmental regulation intensity mainly enhances green technology innovation capability by strengthening the pure technological efficiency of green technology innovation. Second, when regulation intensity is between the first and second thresholds, the threshold values of the two models are somewhat different. Yet the threshold value of Model (A) is basically close to that of **Table 6**. The estimation coefficient of Model (A) is significantly positive, while that of Model (B) is negative but not statistically significant. This indicates that when the regulation intensity is at the medium level, environmental regulation mainly influences green technology innovation capability by acting on green technology progress. In the end, when regulation intensity spans the second threshold, the interval of Model (A) is basically the same as that of **Table 6**, differing from the starting point value of Model (B). The estimation coefficient of Model (A) is significantly negative, while that of Model (B) is positive but not statistically significant. This result shows that when regulation intensity is relatively high, environmental regulation intensity will hinder the green technology progress index and thus restrain improvement of green technology innovation capability.

As indicated by the above comparative analysis, when the regulation intensity is relatively low, it can enhance the green technology innovation capability, but this enhancement is mainly realized by improving pure technological efficiency. When regulation intensity is medium, improving environmental regulation intensity can promote green technology innovation capability by enhancing the progress of green technology. When environmental regulation intensity is high, increasing environmental regulation intensity will inhibit the improvement of the green technology innovation capability by hindering the green technology progress. This result shows that, in terms of enhancing green technology innovation capability, high-intensitive environmental regulation is not necessarily appropriate. Nor is excessively low-intensitive environmental regulation effective enough. Medium regulation intensity is optimal.

CONCLUSION AND ENLIGHTENMENT

To examine the possible non-linear relationship between environmental regulation and green technology innovation capability, the paper applies the SBM directional distance function and the global Malmquist–Luenberger index to measure the green technology innovation GML index. This study is based on data from 28 Chinese manufacturing industries (excepting waste resources and waste materials recycling, handicrafts, and other manufacturing industries) from 2004 to 2014. We constructed a non-linear threshold model with environmental regulation as the threshold variable to carry out our empirical analysis.

As indicated by this study, overall, when regulation intensity crosses the threshold limit, there is a significant difference between the impacts of environmental regulation on green technology innovation capability. Specifically, when the regulation crosses from medium intensity to a higher intensity, the effect of environmental regulation on green technology innovation turns from positive to negative. As indicated by the estimation coefficient, there is an inverted U-shaped relationship between environmental regulation and green technology innovation capability. As implied by the index decomposition, environmental regulation's influence on the green technology progress index is represented by a significant inverted N shape. In terms of technological efficiency, when environmental regulation is in the first interval, improving regulatory intensity can significantly increase the pure technological efficiency of green technology innovation, but after it crosses the first threshold, improving environmental regulation intensity does not have a significant impact on enhancing the pure technological efficiency of green technology innovation. This means that environmental regulation's effect on the pure technological efficiency of green technology innovation is only significantly positive at a relatively low regulation intensity interval. As shown by this comparative analysis, when regulation intensity is relatively low, the improvement of green technology innovation capability mainly relies on pure technological efficiency. When regulation intensity is moderate, as environmental regulation is improved, the enhancement of green technology innovation capability primarily relies on technological progress. In an intensive regulation environment, further environmental regulation will inhibit technological progress and reduce technical efficiency, which will lead to declining green technology innovation capability. This demonstrates that environmental regulation plays the best role in promoting green innovation capability when the regulation intensity is in the medium interval.

Finding and exploring the role played by environmental regulation in enhancing green technology innovation capability in the manufacturing industry is the key to promote the coordinated development of continued industrialization and resources and environment. As shown by the conclusions obtained in this study, rationally formulating environmental regulation intensity and improving environmental regulation quality is of positive significance to strengthening the green technology innovation capability of the Chinese manufacturing industry. Meanwhile, we also believe that it is the future research direction to explore and further identify the reasonable environmental regulation intensity of the manufacturing industry.

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