AIMS Green Finance

Green Finance, 4(4): 387–410.
DOI: 10.3934/GF.2022019
Received: 23 August 2022
Revised: 18 October 2022
Accepted: 24 October 2022
Published: 26 October 2022

http://www.aimspress.com/journal/GF

Research article

Path to green development: the role environmental regulation and labor skill premium on green total factor energy efficiency

Siyu Ren[1,2], **Haitao Wu**[3,4,*]

[1] School of Economics, Nankai University, Tianjin 300071, China
[2] Center for Transnationals' Studies of Nankai University, Tianjin, China
[3] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China
[4] Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China

* **Correspondence:** E-mail: haitao.kungfuer@gmail.com.

Abstract: Improving energy efficiency is critical to breaking the resource curse. Using the GML Productivity Index, we measured the China's green total factor energy efficiency (GTFEE) and systematically explored the effects of environmental regulations on GTFEE. This article focuses on the threshold effect of environmental regulation (ER) on GTFEE at different skill premium levels. The conclusion shows that the impact of ER on GTFEE is expressed as a U-shaped relationship. ER can not only directly increase the skill premium, but also indirectly improve the GTFEE by increasing the skill premium. In addition, the threshold effect analysis suggests that skills premiums can enhance the role of ER in promoting GTFEE. Based on a new perspective on labor skills premiums, this study analyzes the mechanisms of environmental regulation to promote GTFEE, which has enlightening significance for improving the pollution control effect of ER and promoting carbon neutrality in China.

Keywords: environmental regulation; skill premium; energy efficiency; threshold effect; China

JEL Codes: K23, Q40, Q55

1. Introduction

In the past few decades, human economic activities have become more frequent. With the widespread use of fossil fuels, various extreme weather events caused by greenhouse gas emissions have frequently threatened the environment, ecological diversity, and human health (Rosa and Dietz, 2012; Ren et al., 2021; Hao et al., 2021). Extreme climate change is one of the most serious survival problems in humans (McMichael, 2013; Yang et al., 2021a; Meierrieks, 2021). The climate problem has been mainly caused by the economic growth of developed countries since the industrialization era. Although these countries have gotten rid of poverty (Wang and Shen, 2016), the vast majority of developing countries still need to rely on rapid economic growth and industrialization to improve living standards for their citizens (Ravindra et al., 2019; Shao and Yang, 2014). The global warming caused by the massive consumption of fossil energy and the environment destruction make human existence suffer from the dual threats of energy scarcity and environmental damage. For China, since the establishment of the market economy, the high GDP growth has created the material conditions for residents to live on, but it has also put pressure on ecology (Wu et al., 2021; Yang et al., 2021b). Manufacturing is an important pillar of national economy and a major industry that causes pollution in China. For a long time, although the development mode that relies on increasing the input of production factors to drive economic growth has brought China a considerable trade surplus, the "ecological deficit" has caused China to suffer from increasingly serious problems of resource depletion and environmental pollution. In 2018, the added value of China's manufacturing accounted for 31.9% of GDP, while energy consumption accounted for about 70%. The energy intensity is much higher than that of developed countries. China's manufacturing energy consumption increased from 809 million tons to 2.684 billion tons, with an average annual growth of 6.51% during the period 20002019. Huge energy consumption and inefficient use of energy have brought serious environmental pollution, making China's environmental performance index ranked at the bottom of the world. However, as China's industrialization and urbanization have not yet been fully completed, energy consumption may continue to grow for a long time, and the coal based energy pattern cannot be fundamentally changed in the short term (Liu et al., 2022). Consequently, improving the energy efficiency of the manufacturing is an inevitable path to curb the sharp increase in energy consumption. Moreover, it is directly related to the changes in residential environment and the sustainable development of human beings.

Energy efficiency (EE) covers single factor and total factor energy efficiency (Yao et al., 2021). Single factor EE is the ratio of energy input to output (energy consumption per unit of GDP), but it ignores the mutual substitution relationship between input variables such as labor and capital and energy input. To this end, scholars have also begun to incorporate pollutant emissions into the calculation of EE, and proposed the concept of green total factor energy efficiency (GTFEE). GTFEE is the improvement of single factor energy efficiency, which is measured by the ratio of target energy input to actual energy input (Hu and Wang, 2006). It considers the substitution relationship between input factors and can more comprehensively reflect the green growth quality of economic development. In order to improve GTFEE, China has implemented a carbon emission trading market, which aims to use the carbon quota system to control pollution emissions and promote sustainable growth of China's manufacturing. Moreover, some financial subsidies, tax relief, pollution control investment, and green financial measures have been implemented to reduce the cost of low-carbon transformation of the manufacturing industry and broaden financing channels (Zheng et al., 2022). These measures demonstrate China's determination to maintain ecologically sustainable development and become an important way to lead the green transformation and development of China's manufacturing industry (Figure 1).

Theoretical research believes that strict environmental regulation policies are an important approach to achieve sustainable development (Millimet and Roy, 2016; Zhu et al., 2014). Promoting technological progress and adjusting the industrial structure are crucial path to solve the problem of high pollution and high energy consumption in the industrial sector (Yang et al., 2018). Although environmental supervision policies can force enterprises to produce sewage equipment and reduce the unit energy consumption of products, this also increases business operating costs and reduces R&D investment in the short term (Ambec et al., 2013). Therefore, environmental regulations may inhibit productivity growth and the expansion of production scale (Chen et al., 2021; Wu et al., 2020a). In addition, some literature indicated that the correlation between ER and GTFEE is nonlinear (Wang et al., 2021). It can be seen that the relationship between ER and GTFEE is uncertain, and requires further empirical testing.

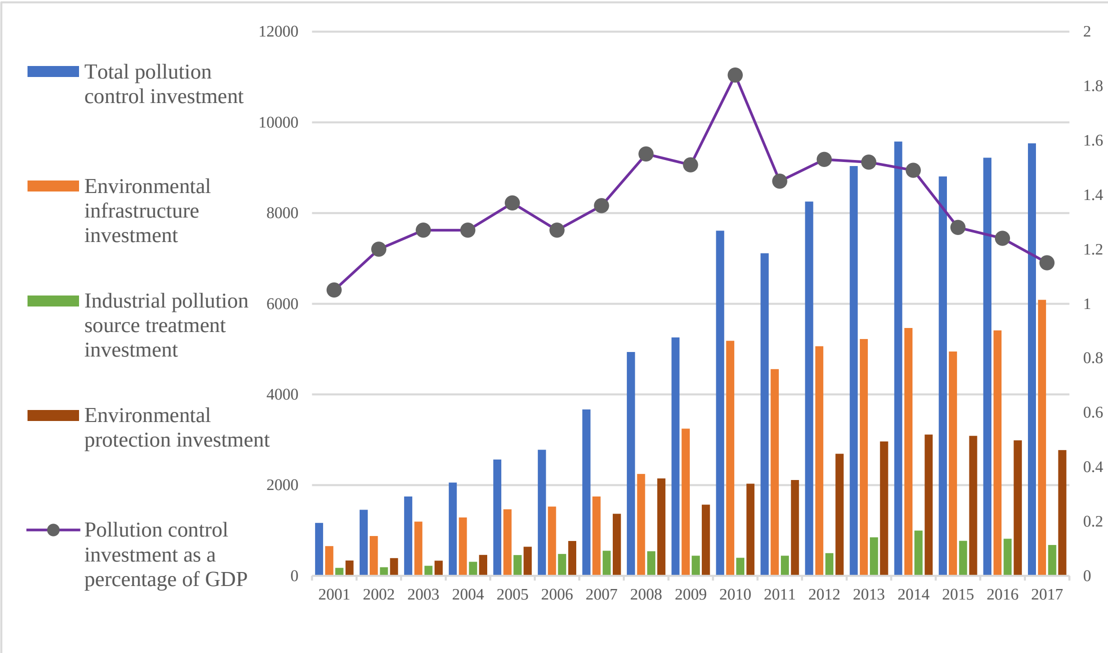

Figure 1. China's environmental governance investment level (left scale unit: 100 million yuan) and proportion of GDP (right scale unit: %) during 2001 to 2017 (unit: year).

ER is important to ensure that promoting technological progress with low-skilled bias (Song et al., 2021). Due to the complementary effects between different skilled workers, the strengthening of environmental regulations will increase the demand for high-skilled labor in companies, pushing up the skill premium level between high-skilled and low-skilled labor (Yu et al., 2017). With the demise of the demographic dividend, China is in desperate need of high-skilled workers to drive the green upgrading of manufacturing. Improving the efficiency and sustainability of GTFEE of manufacturing can help China get rid of the resource shortage and pollution (Cai et al., 2019). In addition, the skill premium promotes the accumulation of human capital in China, which has increased the supply of high-skilled workers in the labor market, and thus realized the transformation of China's manufacturing industry from factor-dependent development to innovation-driven development.

The present research makes three major contributions. First, constructed a general analytical framework that includes environmental regulations, skills premiums, and GTFEE. Base on the visual angle of skill premium, this work deconstructs the internal mechanism of ER to GTFEE. Second, the EBM-DDF model that can incorporate undesired output are used to measure the GTFEE in China. It effectively avoids the lack of the original ratio information of the SBM model ignoring the efficiency frontier projection value, and makes the measurement results more reliable. Third, some literature demonstrates the linear impact of ER on GTFEE, but the effect of ER may show nonlinear characteristics under the influence of some potential threshold factors. Therefore, we adopt the more advanced dynamic threshold method to test the influence of ER on GTFEE under different skill premium levels. It plays an important role in spatial heterogeneity analysis and response to endogenous problems.

The remaining chapters are as follows. Section 2 is a literature review. Mechanistic analysis is reflected in the section 3. Section 4 introduces the data source, variable selection, and model setting. Sections 5 discusses the results, and we finally offer conclusions in section 6.

2. Review of the literature

2.1. Literature study on environmental regulation

Through the formulation of ER, the government has effectively prevented and controlled pollutant emissions and solved the dilemma of economic development and pollution (Callan and Thomas, 2013). For the type of environmental regulation, the command-and-control type regulations adopt more direct methods to prevent and control environmental pollution by formulating pollution standards and limiting the concentration of pollutants (Blackman and Liu, 2018). Because of the obvious effectiveness of command-and-control type regulations, it is widely used by local governments. Market-based type regulation mainly promotes enterprises to actively carry out environmental pollution control activities through market-oriented supervision mechanisms. (Blackman et al., 2018). It includes pollutant discharge fees, environmental protection subsidies, pollutant discharge permits and other regulatory tools. Compared with command-and-control type, market regulation is cheaper and may produce efficient policy effects (Copeland and Taylor, 2013). Voluntary environmental regulations are mainly manifested in ways such as eco-labeling and letters and visits (Blackman, 2008). For example, the US environmental protection work largely relies on citizen environmental litigation (Becker et al., 2013). With the intensification of environmental pollution and the continuous advancement of environmental protection policies, scholars have mostly focused on the command-based and market-based regulation, while ignoring the impact of voluntary ER (Guo et al., 2021).

There exists no uniform measurement method for regulations in the previous literature, which makes it difficult to obtain environmental regulation indicators. Overall, the measurement methods of environmental regulations roughly include four categories: (1) Cost indicators. It is usually used to measure the cost of abatement and is widely used by scholars in the study of environmental policies. (2) Input indicators. It includes environmental protection fiscal expenditure, pollution control investment (Naso et al., 2017). Based on the amount of investment in pollution control, some scholars have conducted a cross-provincial comparative analysis of environmental protection tools (Zhang et al., 2020a). (3) Performance indicators are measured by the effectiveness of pollution control (Alpay et al., 2010). (4) Indicator system. Based on the three main pollutants indicators, Wu et al. (2020b) employed the entropy method to calculate the comprehensive regulation indicators.

2.2. Research on environmental regulations and pollution

Regarding the pollution control effect of environmental control, the existing literature has analyzed from different perspectives and formed some basic viewpoints. The first point of view, from the perspective of economic scale effect, believes that environmental regulation suppresses pollution emissions by reducing economic activities (Ouyang et al., 2019). However, in the case of weak regulation, high supervision costs, and asymmetric information, environmental regulation could exacerbate pollution problems by expanding the size of the hidden economy. For technological innovation perspective, reasonable ER under dynamic adjustment can promote the R&D and application of clean technologies, which is conducive to promoting the improvement of GTFEE and forming a "Porter effect" (Zhou et al., 2020). Whereas, due to the impact of ER, the cost of enterprises will rise sharply in the short term, which may squeeze research and development funds, inhibit productivity growth (Jin et al., 2019). From the perspective of industrial structure adjustment, believes that increasingly tight environmental regulations have further eliminated high-polluting industries, optimized the function of resource allocation, and ultimately promoted energy conservation and pollution reduction (Zhang et al., 2019; Chen et al., 2019). Fourth, the impact of ER on environmental pollution may be non-linear and complex. The effectiveness of ER is not only related to economic factors such as income and industry heterogeneity, but also to institutional factors such as the quality of government governance and corruption (Zhang et al., 2020b; Chen et al., 2018; Hassan et al., 2020). Finally, some scholars pointed out that once the endogenous issues of environmental protection policies are not fully considered, the effects of environmental governance fail to be accurately identified (Millimet and Roy, 2016).

2.2. Research on environmental regulations and skill premium

The existing literature focuses on the influence of ER on economic growth (Zhang, 2016), technological innovation (Mbanyele and Wang, 2022), and industrial transformation (Liu et al., 2016), while the relationship between ER, labor wage and skill premium is rarely involved. Regarding the impact of labor wages, some studies suggested that ER increases the cost burden of enterprises and reduces the profitability of enterprises, thus forcing enterprises to adjust wage levels and suppress wage growth (Liu et al., 2021). ER can restrain real wage increases for workers by raising consumer prices (Hazilla and Kopp, 1990). However, Berman and Bui (2001) found that ER can increase labor demand in U.S. refineries, indirectly leading to higher wages in this industry. The impact of ER on wages has obvious regional heterogeneity, industry heterogeneity, and time heterogeneity (Mishra and Smyth, 2012; Liu and Wang, 2020). Although ER reduces the wages of workers in heavy pollution industries in the short term, ER can improve the average wage growth rate in high-tech and low-energy-consuming industries in the long run (Li and Chen, 2019). Kim et al (2015) found that ER has the greatest impact on wage levels in industries such as petroleum, coal, chemical and paper products. On the wage skill premium, some scholars believed that the environment increases pollution input and promotes the upgrading of green technology, which indirectly affects the demand for skilled workers and the skill premium (Wang et al., 2021). This effect can be explained from the cost effect and profit perspective. From the perspective of production costs, facing strict environmental policies, restricted companies have to invest in the treatment of pollutants, eliminate outdated production equipment and improve production processes, which directly increases the cost of pollution control (Shu et al., 2021).

Enterprises can shift environmental costs by controlling the scale of production and reducing wages (Mishra and Smyth, 2012). In addition, environmental costs increase corporate profits and capital investment in research and development, which reduces the need for highly skilled labor (Song et al., 2021). Some studies, however, have also found that the high cost brought by ER also drives firms to implement green technology R&D activities. It in turn increases the demand for high-skilled labor to match R&D activities, and raises the skill premium (Zheng et al., 2022).

3. Influence mechanisms analysis

3.1. Environmental regulation on GTFEE

The deterioration of the ecological environment not only damages people's physical and mental health, but also threatens the green growth of the manufacturing. Green manufacturing can lead industrial green and low-carbon transformation and optimize regional ecological quality. At present, environmental regulation has become an important means to promote the green development of the manufacturing industry. The direct impact of ER on manufacturing GTFEE is explained by cost effect and innovation compensation effect.

ER refers to the legal norms formulated by the government to improve environmental quality. In the early stage of regulatory policy, to meet the corresponding environmental standards, enterprises usually choose to improve production and emission reduction equipment and increase environmental protection investment (Fan et al., 2022). When production costs are constrained, this behavior diverts productive investment, reduces corporate output, and hinders the optimization of the energy structure. Facing the government's environmental intervention, enterprises are forced to invest resources originally used for production activities into environmental governance or emission reduction activities, which indirectly changes the optimal decision of enterprises (Qiu et al., 2021). Moreover, the implementation of environmental clauses also constrains the management and decision-making behavior of enterprises, and increases management costs. The early neoclassical theory believed that the increase of costs would cause the loss of enterprise productivity and competitiveness, and hinder the transformation of enterprises (Greenstone et al., 2012). Technological innovation is crucial to the improvement of GTFEE (Acemoglu et al., 2012). To cut costs and maintain the original profit level as much as possible, companies may also reduce capital investment in technology R&D and green innovation, indirectly reducing the level of corporate GTFEE. In addition, the potential barriers to entry formed by environmental costs will also increase business risks (Reinhardt, 1999), which disrupts business operations and reduces green energy efficiency. Hence, this paper argues that cost effects may negatively affect GTFEE levels in the early stage of ER.

In the long run, to better carry out production activities under environmental regulation, enterprises will try to improve green energy efficiency through green technology innovation (Li and Chen, 2019). Technological progress is the core driving force of economic growth and one of the sources of power for green total energy efficiency growth (Acemoglu et al., 2012). Once environmental policy becomes a long-term mandatory and sustainable administrative means, enterprises will actively innovate green technologies and enhance their competitiveness to offset rising costs and falling profits caused by environmental regulation. On the one hand, Long-standing ER can enhance the environmental awareness of enterprises and guide enterprises to pay attention to technological progress and innovation (Cai et al., 2020; Xu et al., 2022). On the other hand, technological innovation can also reduce the uncertainty of enterprises' investment in environmental governance (Lv et al., 2021). Once firms are unable to gain innovation gains and competitive position by circumventing environmental investments, they will also proactively increase the impetus for innovation and technological progress (Wang et al., 2018). In addition, the entry barriers and business risks caused by environmental costs will strengthen the competition mechanism between enterprises. To maintain a competitive advantage, enterprises will increase investment in innovation, triggering indirect innovation compensation effects. It reduces energy consumption and energy intensity and increases corporate GTFEE. Therefore, the implement of ER encourages enterprises to carry out green innovation on the basis of internalizing environmental costs in the long run.

Hypothesis 1: The impact of ER on GTFEE is represented by a "U"-shaped relationship.

3.2. Environmental regulation and the skills premium

ER mainly affects skill premium through cost effect, innovation compensation effect and job creation effect. (1) Cost effect. The traditional hypothesis suggests that the increase in environmental costs may arise the "crowding out effect" of R&D investment, inhibit the technological innovation of enterprises and reduce the demand for skilled labor. Enterprises may transfer environmental costs by reducing wages. The wage of skilled labor is higher than that of unskilled labor. When the same wage is reduced, the ratio of skilled labor to unskilled labor will still increase, that is, the skill premium will increase. (2) Innovation compensation effect. The "Porter Hypothesis" holds that a reasonable intensity of ER can effectively stimulate the innovation motivation of enterprises and generate innovation compensation advantages. The high cost of ER will stimulate the R&D motivation of enterprises, and promote the green transformation of production equipment (product innovation or process innovation). It will undoubtedly increase the demand for skilled labor, lead to an increase in the price of skilled labor, and increase the skill premium. (3) Job creation effect. ER can lead to an increase in the prices of resources and energy-based factors. In this case, enterprises will tend to use labor factors to replace relatively high-priced resource and energy-based factors, thereby producing employment creation effects. Meanwhile, higher ER forces enterprises to implement cleaner production and pollution control activities, which increases the demand for skilled labor and raise the skill premium. Therefore, we propose the following research hypothesis.

Hypothesis 2: ER can improve the level of labor skill premiums.

3.3. Environmental regulation, skills premium and GTFEE

ER can improve GTFEE by raising the level of the skills premium. (1) Hypothesis 1 put forward that ER can directly promote the improvement of manufacturing GTFEE. ER increases the production cost of high-pollution industries, forces enterprises to innovate green production technologies, thereby promoting the improvement of GTFEE in the manufacturing industry. (2) The improvement of ER increases the skill premium of enterprises. When ER are tightened, the rapid development of the environmental protection industry increases employment opportunities for skilled labor, widening the wage gap between skilled labor and unskilled labor, thereby increasing the skill premium. (3) ER has a positive impact on manufacturing GTFEE through skill premium. When the level of ER increases, the increase in the demand for skilled labor will lead to an increase in the skill premium. The skill premium increases the supply of skilled labor, provides sufficient human capital for green technology research and development. Besides, ER can accelerate the transformation of unskilled labor into skilled labor and improve the overall quality of the labor force, thereby promoting green development capabilities of the manufacturing. In addition, under different skill premium levels, the impact of ER on manufacturing GTFEE is also different. Since the supply of skilled labor is low, the effect of ER on the manufacturing GTFEE is small when the level of skill premium is low. As the level of technology premium increases, ER increases the cost of pollutant emission of manufacturing enterprises, and improves the enthusiasm of enterprises to conduct R&D and innovation in pollution reduction. By raising the skill premium level, ER can increase the supply of skilled labor and guide the knowledge update of technical talents in the industry, so as to better play the role of ER in promoting GTFEE in manufacturing. We propose the following research hypothesis.

Hypothesis 3: Labor skill premium plays a moderation effect and threshold effect in the impact of ER on GTFEE.

4. Methods design

4.1. Model settings

4.1.1. Baseline model

To analyze the potential nonlinear effect of environmental regulations on GTFEE, the quadratic term of ER is adopted to our baseline model as follow:

$$GTFEE_{it} = \alpha_0 + \alpha_1 GTFEE_{it-1} + \alpha_2 ER_{it} + \alpha_3 ER_{it}^2 + \sum_{k=1}^{6} \delta_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

where subscript i is industry, and t represent year. $GTFEE_{it}$ is the green total factor energy efficiency, $GTFEE_{it-1}$ represents the lag term of GTFEE. The main control variables include skill premium (SP_{it}), capital structure (CS_{it}), property rights structure (PRS_{it}), energy consumption structure (ECS_{it}), technological innovation (TI_{it}), trade import (IM_{it}), sales scale (SS_{it}) and trade export (EX_{it}). α_0, α_1, α_2, …, α_n are the coefficients. μ_i and θ_t are industry and year fixed effects, and ε_{it} stands for the error term.

4.1.2. Mediation effect model

To test whether the environmental regulation can increase the GTFEE through skill premiums, following Ren et al., (2022), we perform a step-by-step regression with equations (2), (3), and (4).

$$GTFEE_{it} = \gamma_0 + \gamma_1 ER_{it} + \sum_{k=1}^{6} \gamma_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$Med_{it} = \vartheta_0 + \vartheta_1 ER_{it} + \sum_{k=1}^{6} \vartheta_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

$$GTFEE_{it} = \varphi_0 + \varphi_1 ER_{it} + \varphi_2 Med_{it} + \sum_{k=1}^{6} \varphi_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (4)$$

Among them, Med_{it} is the mediating variable (SP_{it}). Formula (2) tests the impact of ER on GTFEE; formula (3) estimates the effect of ER on skill premium; formula (4) further examines whether skill premium plays a mediating role between ER and the GTFEE.

4.1.3. Threshold panel model

We further analyze threshold effect between ER and GTFEE. Referring to the research methods of Wu et al. (2020b), the dynamic threshold model is set as follows.

$$GTFEE_{it} = \beta_0 + \beta_1 ER_{it} \bullet I(q_{it} \leq \gamma) + \beta_2 ER_{it} \bullet I(q_{it} > \gamma) + \beta_3 X_{it} + \lambda_i + \varepsilon_{it} \quad (5)$$

4.2. Variables selected

4.2.1. GTFEE

Presently, some statistical methods such as Solow growth kernel algorithm, and data envelopment analysis (DEA) are used to quantify GTFEE (Jia et al., 2021; Su et al., 2021). Among them, the data envelopment analysis method demonstrates the tremendous potential of a nonparametric method to handle efficiency calculations that do not have fixed data units and do not specify production function form (Ren et al., 2022). The Epsilon-Based Measure (EBM) model not only distinguishes the magnitude of decision unit efficiency, but also tackles the potential for desired and undesired outputs in the computation process. As such, the EBM model is employed to calculate the GTFEE. The variable measurement method is shown in Table 1.

Table 1. Measured indicators of GTFEE in 2004–2017.

Attribute layer	First-class index level	Method and data source
Input variable	Capital stock (K)	The perpetual inventory method
	labor (L)	The annual average number of employees in industrial firms above designated size
	Energy consumption (E)	The total energy consumption of industrial firms above designated size
Desirable outputs variable	Industrial sales output value	Considering the availability of data, industrial sales output value is used as a substitute variable for expected output.
Undesirable output variable	Chemical oxygen demand (COD)	-
	SO2 emissions (SO2)	-
	Carbon emission (CO2)	Carbon emissions are estimated using 8 commonly used energy consumption and their carbon emission coefficients, carbon oxidation factors and calorific value.
	Solid waste emissions	--

The manufacturing GTFEE is measured by MAXDEA software (Table 2), and decomposed into green technological efficiency (GEFFCH) and green technological progress (GTECH) (see Appendix for specific industry name). The calculation results display that the average value of GTFEE of 27 industries in China's manufacturing is 1.020, indicating that the GTFEE of China's manufacturing has increased by an average of 2% per year. In terms of efficiency decomposition value, the annual average value of GEFFCH is 0.988, and the annual average value of GTECH is 1.037. We found that the green development of the manufacturing mainly benefits from green technological progress rather than green technical efficiency. Therefore, compared with green technology, the efficiency of green technology has great potential for GTFEE. Besides, the GTFEE of 22 sectors has increased, and the efficiency of 5 sectors has decreased. The specific industry name is in the appendix file.

Table 2. The average value of GTFEE.

Industry code	GTFEE	GEFFCH	GTECH	Industry code	GTFEE	GEFFCH	GTECH
M1	0.999	0.955	1.048	M15	1.037	0.998	1.040
M2	0.996	0.971	1.027	M16	0.957	0.968	1.020
M3	1.004	0.978	1.028	M17	1.029	0.984	1.047
M4	1.000	1.000	1.000	M18	1.049	0.996	1.053
M5	1.013	0.966	1.052	M19	1.050	1.002	1.072
M6	1.017	0.982	1.040	M20	1.030	0.984	1.048
M7	0.993	0.977	1.030	M21	1.008	0.969	1.042
M8	1.002	0.999	1.005	M22	1.052	1.001	1.050
M9	1.006	1.000	1.006	M23	1.048	1.004	1.043
M10	1.013	0.978	1.037	M24	1.066	1.006	1.071
M11	0.976	0.988	0.993	M25	1.061	1.000	1.061
M12	1.001	1.000	1.001	M26	1.053	1.000	1.053
M13	1.004	0.967	1.055	M27	1.030	1.000	1.030
M14	1.055	0.996	1.060	M28	1.020	0.988	1.037

4.2.2. Environmental regulation

Although the construction of environmental regulation (ER) index has matured, the measurement of ER at the industry level is still more difficult. Previous studies have used the ratio of pollutant treatment costs to operating income to measure environmental regulation. However, this measurement method cannot truly reflect the burden of pollution control. This article uses the following method to measure environmental regulation (Huang et al., 2018).

$$\text{poc} = \sum_{i=1}^{2} \frac{cos_i}{emi_i} \frac{fac_i}{fac_i + fac_2} \tag{6}$$

where, $\cos_1$ and $\cos_2$ represent the treatment costs of industrial waste water and waste gas; emi_1 and emi_2 represent waste water emissions and waste gas emissions; $\mathrm{fac}_1$and fac_2 represent waste water treatment facilities and waste gas treatment facilities. For the convenience of statistical analysis of the data, based on the division standard of national economic industries (GB/T4754-2011), we divide China's manufacturing sector into 28 sub-sectors. The specific pollution indicators (eg., waste water, waste gas, etc.) in this paper are from China Environmental Yearbook.

4.2.3. Skill premium

Since this article focuses on the analysis of skill premium differences within the manufacturing industry, it is not suitable for division according to the distribution of technical personnel. Reference to the research of Huang et al. (2018), this article treats scientific and technological personnel as skilled laborers. The ratio of the total remuneration of scientific and technological personnel to the number of scientific and technological activities represents the per capita salary of skilled labor. Non-scientific and technical personnel are uniformly regarded as unskilled laborers, which are measured by the difference between the annual average number of all employees and the number of scientific and technical personnel. The average wage of unskilled workers is measured by the ratio of the total wages of the manufacturing industry excluding the wages of scientific and technical personnel to the number of unskilled workers.

4.2.4. Control variables

The capital structure is expressed by the ratio of foreign investment in various industries to paid-in capital (Wang et al., 2018). The number of enterprise patents is used as a proxy variable of the technological innovation. The R&D level of an enterprise is expressed as the ratio of the R&D capital investment in various industries to industrial sales output value (Wei and Liu, 2006). The property right structure is expressed as the ratio of the total assets of state-owned enterprises to the total assets of industrial enterprises (Shen and Lin, 2020). The energy consumption structure is expressed by the ratio of coal consumption to total energy consumption. The level of imports is expressed as the ratio of the value of sub-industry imports to the value of industrial sales. The trade export is expressed by the ratio of the industry's total export value to the industry's total output value. The statistical results of all variables are shown in Table 3.

Table 3. The statistical description of variables.

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
GTFEE	Green energy efficiency	378	1.2575	0.3624	0.4935	2.4932
ER	Environmental regulation	378	15.5953	19.5905	0.2159	113.3026
SP	Skill premium	378	1.4885	0.3802	0.7767	3.2737
CS	Capital Structure	378	0.2863	0.1529	0.0005	0.7638
PRS	Property structure	378	0.1767	0.2231	0.0030	0.9949
ECS	Energy consumption structure	378	0.4576	0.2215	0.0672	0.8566
TI	Technological innovation	378	212.4502	137.9494	22.7476	774.1671
IM	Trade import	378	0.1286	0.2516	0.0009	1.9850
EX	Trade export	378	0.2387	0.3193	0.0046	1.6387
SS	Sales scale	378	19263.01	18112.45	1079.377	86308.14

5. Results and analysis

5.1. Benchmark model

We use the OLS, FE, and generalized least squares (GLS) regression methods to estimate basic model. Additionally, to address endogeneity problem between ER and GTFEE, the GMM method is used to re-estimate equation (1). The results in Table 4 display the significance and coefficient sign of the explanatory variables (ER) show no marked difference, only the coefficient values are different. We focus on the empirical results of the GMM estimation method. From the empirical results, regardless of the estimation method adopted, the coefficient of ER^2 is significantly positive, indicating that the relationship between ER and GTFEE is "U-shaped". This result is consistent with Wu et al. (2020a). Environmental regulation policy leads to an increase in corporate pollution control costs and production factor costs under low-intensity environmental regulation, which produced a "crowding out effect" on innovation investment and technology R&D investment, and indirectly hinders the improvement of GTFEE (Yuan and Xiang, 2018). However, in the long run, to reduce costs and obtain more profits, companies usually take the initiative to develop energy-saving technology R&D, optimize the input structure of factors, and internalize the external costs of environmental regulations. Additionally, under the increasing pressure of economic sustainability, firms tend to use clean energy to replace fossil energy. Therefore, the adjustment of energy structure further promotes the increase of GTFEE.

Table 4. The results of the baseline model.

Variable	OLS	FE	RE	FGLS	GMM
$GTFEE_{it-1}$					0.233^{***}
					(8.934)
ER	-0.075^{***}	-0.065^{***}	-0.062^{***}	-0.030^{***}	-0.022^{**}
	(−4.576)	(−3.334)	(−3.422)	(−3.277)	(−2.017)
ER^2	0.005^{**}	0.006^{***}	0.006^{***}	0.005^{***}	0.006^{***}
	(2.244)	(3.157)	(3.146)	(4.860)	(3.776)
CS	-0.693^{***}	-0.432^{***}	-0.496^{***}	-0.209^{***}	-0.505^{***}
	(−6.446)	(−2.894)	(−3.572)	(−5.218)	(−3.333)
PRS	-0.442^{***}	−0.060	-0.307^{**}	-0.569^{***}	0.530
	(−7.013)	(−0.282)	(−2.209)	(−5.584)	(0.857)
SS	0.149^{***}	0.168^{***}	0.162^{***}	0.162^{***}	0.180^{***}
	(21.672)	(19.081)	(20.760)	(28.617)	(12.789)
ECS	0.430^{***}	−0.077	0.036	−0.071	0.383^{***}
	(6.405)	(−0.742)	(0.391)	(−0.950)	(2.832)
IM	0.131^{**}	0.205^{***}	0.204^{***}	0.079	0.528^{*}
	(2.191)	(2.646)	(2.791)	(1.417)	(1.853)
EX	0.165^{***}	-0.189^{**}	-0.146^{*}	−0.034	−0.357
	(2.941)	(−2.326)	(−1.929)	(−0.532)	(−1.194)
Con	1.086^{***}	1.143^{***}	1.156^{***}	1.145^{***}	
	(18.633)	(14.252)	(14.395)	(20.734)	
R^2/Wald test	0.6573	0.7757	0.7739	1432.72	4143.75
AR(1) /p-Value					−2.28[0.023]
AR(2) /p-Value					−0.47 [0.640]
Hansen Test /p-Value					21.24 [0.968]
N	378	378	378	378	378

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The figures in () are the t-values or z-values; Figures in [] are the p-values. This note also applies to the following table.

5.2. Regression results of environmental regulation on skill premium

To test the impact of ER on skill premium, the OLS, FGLS and GMM models are applied to empirical test the relationship between them. The empirical results point out that ER can increase the level of skill premiums in the labor market (see Table 5). It is consistent with the empirical conclusions of Wang et al. (2021a). An important reason is that Lax environmental supervision policies will not only lead to the expansion of the production scale of polluting industries, but also attract the inflow of polluting industries in developed countries. Pollution industries are mainly labor-intensive industries, which require relatively low skills for workers. Since unskilled workers can adapt to jobs in polluting industries, the expansion of polluting firms will inevitably increase the demand for unskilled workers, thereby reducing the level of skill premiums. With the continuous increase of the environmental regulations intensity, enterprises may think highly of green production and pollutant control in the production process (Yu et al., 2017). Whether it is the upgrading and improvement of the production process or the end pollution control, it is necessary to introduce skilled workers who master the corresponding technology. Therefore, it increases the demand for skilled labor, produces employment substitution effects, and raises the skill premium.

Table 5. The results of ER on skill premium.

Variables	OLS	RE	FGLS	SYS-GMM	DIF-GMM
SP_{it-1}				0.180^{***}	0.055^{***}
				(6.471)	(6.330)
ER	0.042^{***}	0.029^{**}	0.005^{*}	0.076^{***}	0.057^{***}
	(2.925)	(2.314)	(1.705)	(4.620)	(3.951)
CS	0.924^{***}	1.402^{***}	1.008^{***}	0.821^{***}	1.283^{**}
	(3.652)	(6.522)	(12.639)	(3.638)	(2.399)
PRS	1.664^{***}	0.416^{**}	0.028	−0.103	6.729^{***}
	(4.541)	(2.533)	(0.263)	(−0.408)	(5.416)
SS	0.004	−0.012	−0.014	−0.011	0.183^{***}
	(0.254)	(−0.976)	(−1.334)	(−0.401)	(3.058)
ECS	0.560^{***}	0.331^{**}	0.376^{***}	0.107	0.101
	(3.121)	(2.395)	(9.803)	(0.765)	(0.604)
IM	0.355^{***}	0.204^{*}	0.325^{***}	0.173	-0.726^{***}
	(2.668)	(1.751)	(10.325)	(1.443)	(−5.623)
EX	0.211	0.166	-0.076^{**}	0.022	3.047^{***}
	(1.511)	(1.403)	(−2.056)	(0.132)	(5.615)
_cons	0.815^{***}	0.771^{***}	0.980^{***}	0.754^{***}	
	(4.896)	(6.703)	(25.364)	(3.972)	
AR(1) /p-Value				−3.46 [0.001]	−2.49 [0.013]
AR(2) /p-Value				0.30 [0.767]	1.15 [0.251]
Hansen test/p-Value				25.67 [0.962]	24.38 [0.383]
R2/Wald test	0.6762	0.3853	835.54	1146.59	1201.33
N	378	378	378	378	378

5.3. The results of the mediation effect

To study the transmission mechanism between ER and GTFEE, skill premium is used as an intermediary variable to test the influence channel (see Table 6). Specifically, the effect of ER on GTFEE shows "U" shaped relationship. Moreover, the estimated coefficient of ER on the skill premium is significantly positive (0.076), indicating that ER can increase the wage gap between skilled and unskilled workers. And, skill premium can significantly promote GTFEE in column (3). Referring to the analysis criteria of the mediation effect, we believe that ER can indirectly improve GTFEE by increasing the skill premium. This study proves that skill premium plays an important role in environmental governance.

Table 6. Estimation results of the mediation effect.

Variables	(1)	(2)	(3)
	GTFEE	SP	GTFEE
$L.\text{Var}_{it-1}$	0.233^{***}	0.180^{***}	0.250^{***}
	(8.934)	(6.471)	(7.77)
ER	-0.022^{**}	0.076^{***}	-0.036^{***}
	(−2.017)	(4.620)	(−2.61)
ER^2	0.006^{***}		0.008^{***}
	(3.776)		(3.05)
SP			0.047^{**}
			(2.38)
CS	-0.505^{***}	0.821^{***}	-0.817^{***}
	(−3.333)	(3.638)	(−4.21)
PRS	0.530	−0.103	1.185^{**}
	(0.857)	(−0.408)	(2.20)
SS	0.180^{***}	−0.000	0.158^{***}
	(12.789)	(−0.401)	(14.22)
ECS	0.383^{***}	0.107	0.442^{***}
	(2.832)	(0.765)	(3.03)
IM	0.528^{*}	0.173	0.412
	(1.853)	(1.443)	(1.60)
EX	−0.357	0.022	-0.67553^{*}
	(−1.194)	(0.132)	(−1.76)
AR(1) /p-Value	−2.28[0.023]	−3.46 [0.001]	−2.35 [0.019]
AR(2) /p-Value	−0.47 [0.640]	0.30 [0.767]	−0.24 [0.811]
Hansen test/p-Value	21.24 [0.968]	25.67 [0.962]	21.04 [0.970]
Wald test	1201.33	1146.59	5256.51
N	378	378	378

5.4. The results of the threshold model

Table 7. The threshold effect test.

Variable	Model	Threshold value	Wald	P-value	BS
SP	SYS-GMM	1.3571	0.1027***	0.0000	1000
	DIF-GMM	1.3571	0.1027***	0.0000	1000

Table 8. The result of threshold model.

Variable	SYS-GMM	DIF-GMM
$GTFEE_{it-1}$	0.8988***	0.2159***
	(22.21)	(4.33)
CS	−0.2235***	−0.2325
	(−3.20)	(−1.46)
PRS	−0.1529**	−0.3665
	(−2.24)	(−0.90)
SS	0.0276***	0.1241***
	(6.52)	(8.69)
ECS	0.0364	0.1013
	(0.93)	(1.38)
IM	0.0270	0.2846*
	(0.76)	(1.86)
$ER(SP \leq C)$	−0.0192***	0.0123**
	(−2.87)	(2.20)
$ER(SP > C)$	0.0172***	0.0164**
	(4.21)	(2.32)
_cons	0.1840***	0.0103**
	(3.02)	(2.52)
AR(1)	−3.25[0.001]	−2.68[0.007]
AR(2)	1.12[0.262]	1.44[0.150]
Hansen test	25.11[0.836]	25.03[0.993]
Wald test	11711.01	8802.78
N	378	378

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This article uses skill premium as the threshold variable to test the effect of ER on GTFEE under different skill premium levels. Before estimating the model, we test the existence of the threshold. This paper uses the Bootstrap sampling method to estimate thresholds and associated statistics. According to the estimated results in Table 7, Wald statistics with a single threshold is significant at the 1% level, reflecting the skill premium has a single threshold effect. When the skill premium is regarded as a threshold variable, the ER exerts a significant threshold effect on the GTFEE (Table 8). In other words, when skill premium crosses the threshold, there is an increase in the regression coefficient of the ER. This can be attributed to the fact that when the wage gap between skilled and unskilled labor is small, the low skill premium will increase the relative supply of unskilled labor and reduce overall labor costs. It not only makes companies tend to rely on low-cost advantages to increase output, but also leads to a lack of endogenous power for product structure upgrades and green innovation, which reduces the pollution control effect of ER. However, expanding the skill premium will effectively stimulate the supply of highly skilled laborers. It provides high-quality human capital for the company's green technology R&D and product structure upgrade, and better exerts the innovation compensation effect and structural dividend effect of ER. Therefore, with the sharp increase in skill premiums, companies tend to hire highly skilled labor, which increases the possibility of companies engaging in green production and technological innovation. In addition, the conclusion also means that to achieve sustainable development under environmental constraints against the backdrop of a declining demographic dividend, China needs to change its low-cost advantage of labor force and focus on the role of environmental regulation in improving the accumulation of highly skilled workers and human capital.

5.5. Robustness and endogeneity test

Table 9. The result of robustness test.

Variable	(1)	(2)	(3)	(4)	(5)
$GTFEE_{it-1}$	1.009***	0.887***	0.532***	0.356***	0.372***
	(136.565)	(28.020)	(17.246)	(10.847)	(10.367)
ER	−0.034***	−0.030***	−0.015***	−0.013***	−0.014**
	(−17.070)	(−8.193)	(−2.944)	(−3.557)	(−2.308)
ER^2	0.181***	0.208***	0.132***	0.108***	0.105***
	(13.776)	(13.086)	(4.187)	(5.226)	(3.799)
CS	−0.086*	−0.313***	0.098	−0.207	−0.379**
	(−1.915)	(−2.997)	(0.547)	(−1.512)	(−1.998)
PRS		−0.870***	−1.079***	−1.059***	−1.009***
		(−7.403)	(−7.561)	(−6.226)	(−5.174)
SS			0.107***	0.147***	0.149***
			(10.327)	(10.112)	(14.970)
ECS				0.419**	0.619***
				(2.542)	(4.027)
IM					0.559***
					(2.991)
EX					0.002
					(0.008)
Con	−0.020	0.295***	0.362***	0.374***	0.315***
	(−0.931)	(3.501)	(3.782)	(3.417)	(3.959)
Wald test	42047.10	6148.46	5285.86	3500.22	6306.57
AR(1) /P-Value	−3.41 [0.001]	−3.84 [0.000]	−3.35 [0.001]	−3.10 [0.002]	−3.04 [0.002]
AR(2) /P-Value	0.64 [0.523]	0.80 [0.422]	0.93 [0.354]	1.53 [0.125]	1.19 [0.233]
Hansen Test /P-Value	25.75 [0.812]	24.53 [0.825]	23.82 [0.780]	22.28 [0.808]	21.92 [0.785]
N	378	378	378	378	378

(1) Robustness test. The Global Malmquist-Luenberger index is used to recalculate the GTFEE based on the processing method of Kumar (2006) and Arabi et al. (2014). Furthermore, the impact of ER on GTFEE is "U" shaped, indicating that the empirical results are robust (Table 9).

(2) Endogeneity treatment. The panel vector autoregressive model (PVAR) treats all variables as endogenous variables, and analyzes the influence of each variable on other variables in the model without setting the causal relationship between the variables. It treats all variables in the system as endogenous variables to prevent model setting errors and endogenous problems. Therefore, we use the PVAR model to deal with the endogeneity of ER and GTFEE. After performing the panel unit root test and choosing the optimal lag order, we used Monte Carlo simulations 500 times to obtain the impulse response function plot of environmental regulation on GTFEE (Fig. 2). We found that GTFEE exhibits a negative response in the first period and then shifts to a positive shock in the second period under a positive shock of one standard error of environmental regulation. It verifies the "U"-shaped relation between ER and GTFEE.

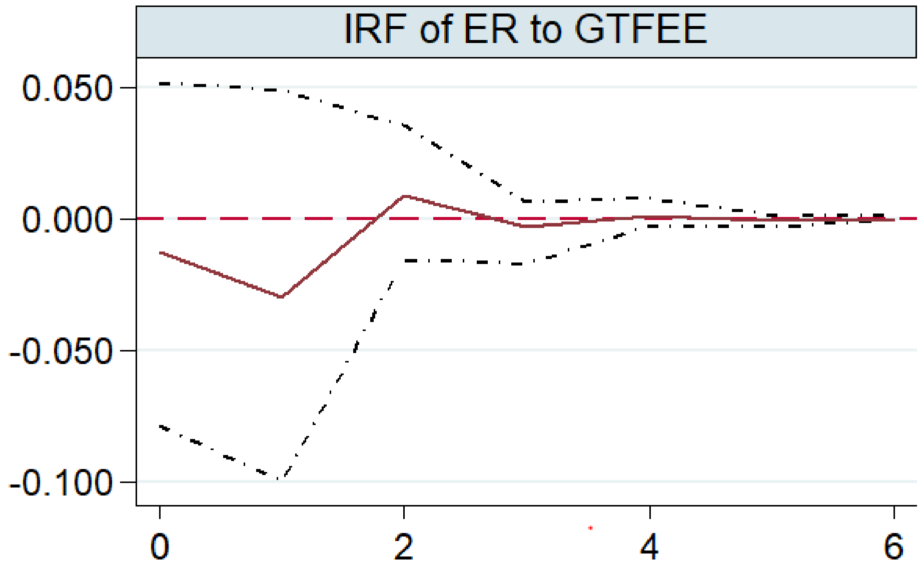

Figure 2. Impulse response function diagram of environmental regulation to GTFEE.

5.6. Quantile regression and heterogeneity analysis

To test whether there is a structural change in the impact of the skills premium on GTFEE, a quantile regression is adopted to measure the effect of skill premium on different GTFEE level. Quantile regression can not only exclude the interference of extreme values, but also fully describe the overall picture of the conditional distribution. To this end, this paper selects 4 representative quantiles (25%, 50%, 75%, and 90%) to estimate the effect of the skills premium on GTFEE. From the change trend of the regression coefficient of skill premium at each quantile, the effect of skill premium on GTFEE is 0.134, 0.169, 0.148, and 0.131 (Table 10). This shows that compared with industries with high GTFEE, the skill premium plays a greater role in promoting GTFEE in industries with low GTFEE.

Table 10. The result of quantile regression.

Variable	0.25	0.50	0.75	0.90
SP	0.134**	0.169***	0.148***	0.131**
	(2.51)	(3.97)	(3.04)	(2.02)
CS	−0.080	−0.535***	−0.637***	−0.836**
	(−0.56)	(−3.70)	(−3.61)	(−2.42)
PRS	−0.424**	−0.516***	−0.485***	−0.629***
	(−2.56)	(−4.81)	(−7.18)	(−4.70)
SS	0.132***	0.133***	0.149***	0.159***
	(13.75)	(11.25)	(11.70)	(8.53)
ECS	0.336***	0.066	0.209***	0.253***
	(3.09)	(0.81)	(3.46)	(2.64)
IM	0.149**	0.137**	0.152**	0.200*
	(2.40)	(2.14)	(2.21)	(1.96)
EX	0.120*	0.034	0.124	0.058
	(1.76)	(0.52)	(1.43)	(0.64)
Con	0.911***	1.445***	1.456***	1.580***
	(5.77)	(14.70)	(18.08)	(10.69)
R^2	0.2727	0.4049	0.5044	0.5214
N	378	378	378	378

Table 11. The result of heterogeneous results.

Variables	Eastern	Central	Western
ER	0.154***	0.001	0.011***
	(9.175)	(0.01)	(3.520)
RD	0.026***	−0.063	−0.001
	(3.031)	(−1.41)	(−0.236)
INFOR	−0.048***	−0.019	0.007***
	(−8.102)	(−1.17)	(7.365)
GIN	−0.010***	−0.006	−0.003***
	(−4.152)	(−0.55)	(−5.454)
FDI	0.007***	−0.005	0.014***
	(5.212)	(−1.02)	(19.251)
_con	0.996***	1.152***	0.399***
	(140.171)	(15.85)	(65.022)
N	99	72	99

Note: RD: investment in technology research and development; INFOR: Internet information technology; GIN: Green investment; FDI: Foreign direct investment

Given the large differences in the manufacturing structure and development level in different regions, the above manufacturing data are replaced by province (or municipalities or autonomous regions) panel data from 2011–2019 to reanalyze the regional heterogeneity of environmental regulation on GTFEE (Table 11). We find that the influence coefficients of ER on GTFEE of the eastern, central and western region are positive, while it is not significant in the central region. The impact coefficient of ER on GTFEE in eastern region is the largest. An important reason is that the eastern coastal areas have convenient transportation, high level of openness, sufficient research and development funds, and strong technological innovation capabilities. These advantages lead to more obvious compensation effect of technical progress in the eastern region.

6. Conclusions

This research tests the correlation between ER, skill premium and GTFEE of the manufacturing. Moreover, we empirically analyze whether the influence of ER on GTFEE is affected by the skill premium. The research findings include: The effect of ER on GTFEE has an "U" shape. Additionally, threshold model results display that the improvement in the degree of skill premium can alleviate the positive effect of ER on GTFEE. We present some insights:

(1) Formulate scientific and appropriate environmental regulation. Due to the relation between ER and GTFEE is characterized by "U" shape, the environmental department needs to flexibly adjust the policy intensity to give full play to the long-term innovative compensation effect of ER. The government should formulate reasonable industrial development policies, improve corporate green energy efficiency, and gradually weaken the "crowding out effect" of ER on the green transition of the manufacturing industry. In addition, there has been an unbalanced economic level in the three regions of China for a long time, and conditions such as natural resources, factor endowments, market environment, and industrial structure are different in different regions. It makes different effects appear under the guidance of the same intensity of ER. It is necessary for each region to flexibly adjust environmental policies in light of the actual level of local economic development. According to the actual situation in different regions, the environmental protection department should introduce detailed pollution control measures to avoid inefficient environmental protection behaviors that disturb the normal operation and production of enterprises and inhibit the enthusiasm of enterprises for production. In particular, our study shows that ER has not yet exerted an innovative compensation effect in the central region. Therefore, to make up for the loss of environmental protection costs caused by corresponding policies, the state should arouse enterprises to engage in green and clean production projects through policy subsidies and special support.

(2) This paper confirms that ER can raise GTFEE through skills premium. Therefore, the government should give full play to the positive effect of environmental regulation on the evolution of the skill structure, and stimulate the transformation of unskilled labor into skilled labor through the technological spillover effect. Besides, the government should encourage the supply of high-skilled labor, optimize the structure of human capital, and provide the ultimate impetus for green development. Besides, the government and enterprises may increase education and training expenditures, improve the professional skills of low-skilled workers. It is conducive to providing high-quality talents for industrial upgrading and technological change, reducing structural unemployment, and achieving a coordination between full employment and environmental governance. The increase of the skill premium can not only upgrade the employment skills structure and encourage the transformation of unskilled labor into skilled labor, but also help to the restrictions on the free flow of labor, and solve the dilemma of the mismatch between labor skills and job demand. To this end, the government needs to establish a complete information docking platform between enterprises and high-skilled labor, so as to avoid the waste of labor resources caused by asymmetric employment information. Moreover,

enterprises also need to strengthen income subsidies and skills training for unskilled workers, promote the transformation of unskilled workers into skilled workers, and increase the supply of high-skilled labor. In addition, in the process of implementing environmental policies, the government should pay attention to the issue of income distribution and continuously improve the social security system. In order to minimize the income imbalance and narrow the income gap, the government should pay attention to the heterogeneous impact of industrial upgrading on the remuneration of labor with different skills, and alleviate the wage differentiation and wage inequality of laborers.

Although we have analyzed the effects of the ER and skill premium on GTFEE, manufacturing panel data may not be as accurate as enterprise data. Furthermore, due to sample selection and space constraints, we did not explore the industry heterogeneity of the effects of the ER and skill premium on GTFEE in detail. Therefore, future research can analyze the more microscopic impact of the ER on sustainable economy, or explore the impact of the ER and skill premium on sustainable development in terms of industry heterogeneity. In addition, scholars can also focus on the technology effect of the skill premium.

References

Alpay E, Hari A, Kambouri M, et al. (2010) Gender issues in the university research environment. *Eur J Eng Educ* 35: 135–145.

Ambec S, Cohen MA, Elgie S, et al. (2013) The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? *Rev Environ Econ Pol* 7: 222. https://doi.org/10.1093/reep/res016

Becker RA, Pasurka Jr C, Shadbegian RJ (2013) Do environmental regulations disproportionately affect small businesses? Evidence from the Pollution Abatement Costs and Expenditures survey. *J Environ Econo Manage* 66: 523538. https://doi.org/10.1016/j.jeem.2013.08.001

Berman E, Bui LT (2001) Environmental regulation and productivity: evidence from oil refineries. *Rev Econ Stat* 83: 498510. https://doi.org/10.1162/00346530152480144

Blackman, A. (2008) Can voluntary environmental regulation work in developing countries? Lessons from case studies. *Pol Stud J* 36: 119141. https://doi.org/10.1111/j.1541-0072.2007.00256.x

Blackman A, Li Z, Liu AA (2018) Efficacy of command-and-control and market-based environmental regulation in developing countries. *Annu Rev Resour Econ* 10: 381404. https://doi.org/10.1146/annurev-resource-100517-023144

Cai W, Lai KH, Liu C, et al. (2019) Promoting sustainability of manufacturing industry through the lean energy-saving and emission-reduction strategy. *Sci Total Environ* 665: 2332. https://doi.org/10.1016/j.scitotenv.2019.02.069

Cai X, Zhu B, Zhang H, et al. (2020) Can direct environmental regulation promote green technology innovation in heavily polluting industries? Evidence from Chinese listed companies. *Sci Total Environ* 746: 140810. https://doi.org/10.1016/j.scitotenv.2020.140810

Callan SJ, Thomas JM (2013) *Environmental economics and management: Theory, policy, and applications*. Cengage Learning.

Chen H, Hao Y, Li J, et al. (2018) The impact of environmental regulation, shadow economy, and corruption on environmental quality: Theory and empirical evidence from China. *J Clean Prod* 195: 200214. https://doi.org/10.1016/j.jclepro.2018.05.206

Chen X, Chen YE, Chang CP (2019) The effects of environmental regulation and industrial structure on carbon dioxide emission: a non-linear investigation. *Environ Sci Pollut Res* 26: 3025230267. https://doi.org/10.1007/s11356-019-06150-6

Chen X, Fu Q, Chang CP (2021) What are the shocks of climate change on clean energy investment: A diversified exploration. *Energy Econ* 95: 105136. https://doi.org/10.1016/j.eneco.2021.105136

Copeland BR, Taylor MS (2013) *Trade and the Environment*. Princeton University Press.

Fan M, Yang P, Li Q (2022) Impact of environmental regulation on green total factor productivity: a new perspective of green technological innovation. *Environ Sci Pollut Res* 29: 116. https://doi.org/10.1007/s11356-022-19576-2

Guo X, Fu L, Sun X (2021) Can Environmental Regulations Promote Greenhouse Gas Abatement in OECD Countries? Command-and-Control vs. Market-Based Policies. *Sustainability* 13: 6913. https://doi.org/10.3390/su13126913

Hao Y, Ba N, Ren S, et al. (2021) How does international technology spillover affect China's carbon emissions? A new perspective through intellectual property protection. *Sust Prod Consumption* 25: 577590. https://doi.org/10.1016/j.spc.2020.12.008

Hao Y, Guo Y, Wu H (2022) The role of information and communication technology on green total factor energy efficiency: Does environmental regulation work? *Bus Strategy Environ* 31: 403424. https://doi.org/10.1002/bse.2901

Hassan ST, Khan SUD, Xia E, et al. (2020) Role of institutions in correcting environmental pollution: An empirical investigation. *Sust Cities Soc* 53: 101901. https://doi.org/10.1016/j.scs.2019.101901

Hazilla M, Kopp RJ (1990) Social cost of environmental quality regulations: A general equilibrium analysis. *J Polit Econ* 98: 853873. https://doi.org/10.1086/261709

Hu JL, Wang SC (2006) Total-factor energy efficiency of regions in China. *Energy Policy* 34: 32063217. https://doi.org/10.1016/j.enpol.2005.06.015

Huang QH, Hu JF, Chen XD (2018) Environmental regulation and green total factor productivity: Dilemma or win-win. *China Popul Resour Environ* 28: 140149.

Jia S, Qiu Y, Yang C (2021) Sustainable Development Goals, Financial Inclusion, and Grain Security Efficiency. *Agronomy* 11: 2542. https://doi.org/10.3390/agronomy11122542

Jin W, Zhang HQ, Liu SS, et al. (2019) Technological innovation, environmental regulation, and green total factor efficiency of industrial water resources. *J Clean Prod* 211: 6169. https://doi.org/10.1016/j.jclepro.2018.11.172

Kim RE, Bosselmann K (2015) Operationalizing sustainable development: ecological integrity as a grundnorm of international law. *Rev Eur Comp Int Environ Law* 24: 194208. https://doi.org/10.1111/reel.12109

Li P, Chen Y (2019) The influence of enterprises' bargaining power on the green total factor productivity effect of environmental regulation—evidence from China. *Sustainability* 11: 4910. https://doi.org/10.3390/su11184910

Lin J, Xu C (2017) The impact of environmental regulation on total factor energy efficiency: A cross-region analysis in China. *Energies* 10: 1578. https://doi.org/10.3390/en10101578

Liu H, Lei H, Zhou Y (2022) How does green trade affect the environment? Evidence from China. *J Econ Anal* 1: 127.

Liu M, Tan R, Zhang B (2021) The costs of "blue sky": Environmental regulation, technology upgrading, and labor demand in China. *J Dev Econ* 150: 102610. https://doi.org/10.1016/j.jdeveco.2020.102610

Liu Y, Wang J (2020) Environmental pollution, environmental regulation, and labor income share.

Environ Sci Pollut Res 27: 4516145174. https://doi.org/10.1007/s11356-020-10408-9

Lv C, Shao C, Lee CC (2021) Green technology innovation and financial development: Do environmental regulation and innovation output matter? *Energy Econ* 98: 105237. https://doi.org/10.1016/j.eneco.2021.105237

Mandal SK (2010) Do undesirable output and environmental regulation matter in energy efficiency analysis? Evidence from Indian cement industry. *Energy Policy* 38: 60766083. https://doi.org/10.1016/j.enpol.2010.05.063

Mbanyele W, Wang F (2022). Environmental regulation and technological innovation: Evidence from China. *Environ Sci Pollut Res* 29: 1289012910. https://doi.org/10.1007/s11356-021-14975-3

McMichael AJ (2013) Globalization, climate change, and human health. *N Engl J Med* 368: 13351343. https://doi.org/10.1056/NEJMra1109341

Meierrieks D (2021) Weather shocks, climate change and human health. *World Dev* 138: 105228. https://doi.org/10.1016/j.worlddev.2020.105228

Millimet DL, Roy J (2016) Empirical tests of the pollution haven hypothesis when environmental regulation is endogenous. *J Appl Econometrics* 31: 652677. https://doi.org/10.1002/jae.2451

Mishra V, Smyth R (2012) Environmental regulation and wages in China. *J Environ Plann Manage* 55: 10751093.

Naso P, Huang Y, Swanson T (2017) The porter hypothesis goes to china: Spatial development, environmental regulation and productivity. *Cies Res Pap*.

Ouyang X, Shao Q, Zhu X, et al. (2019) Environmental regulation, economic growth and air pollution: Panel threshold analysis for OECD countries. *Sci Total Environ* 657: 234241. https://doi.org/10.1016/j.scitotenv.2018.12.056

Qiu S, Wang Z, Geng S (2021) How do environmental regulation and foreign investment behavior affect green productivity growth in the industrial sector? An empirical test based on Chinese provincial panel data. *J Environ Manage* 287: 112282. https://doi.org/10.1016/j.jenvman.2021.112282

Ravindra K, Rattan P, Mor S, et al. (2019) Generalized additive models: Building evidence of air pollution, climate change and human health. *Environ Int* 132: 104987. https://doi.org/10.1016/j.envint.2019.104987

Reinhardt F (1999) Market failure and the environmental policies of firms: Economic rationales for "beyond compliance" behavior. *J Ind Ecol* 3: 921. https://doi.org/10.1162/108819899569368

Ren S, Hao Y, Wu H (2021) How Does Green Investment Affect Environmental Pollution? Evidence from China. *Environ Resour Econ* 81: 2551. https://doi.org/10.1007/s10640-021-00615-4

Ren S, Liu Z, Zhanbayev R, et al. (2022) Does the internet development put pressure on energy-saving potential for environmental sustainability? Evidence from China. *J Econ Anal* 1: 81101.

Rosa EA, Dietz T (2012) Human drivers of national greenhouse-gas emissions. *Nat Clim Change* 2: 581586. https://doi.org/10.1038/nclimate1506

Shao S, Yang L (2014). Natural resource dependence, human capital accumulation, and economic growth: A combined explanation for the resource curse and the resource blessing. *Energy Policy* 74: 632642. https://doi.org/10.1016/j.enpol.2014.07.007

Shen X, Lin B (2020) Policy incentives, R&D investment, and the energy intensity of China's manufacturing sector. *J Clean Prod* 255: 120208. https://doi.org/10.1016/j.jclepro.2020.120208

Shu K, Lu Y, Yu Kuai, et al. (2021). Influences of environmental regulations on skill premium: mediating effect of industrial structure optimization. *Environ Econ Pol Stud* 23: 245273.

https://doi.org/10.1007/s10018-020-00288-1
Song M, Xie Q, Wang S, et al. (2021). Intensity of environmental regulation and environmentally biased technology in the employment market. *Omega* 100: 102201. https://doi.org/10.1016/j.omega.2020.102201
Su Y, Li Z, Yang C (2021) Spatial interaction spillover effects between digital financial technology and urban ecological efficiency in China: an empirical study based on spatial simultaneous equations. *Int J Environ Res Public Health* 18: 8535. https://doi.org/10.3390/ijerph18168535
Wang A, Hu S, Lin B (2021) Can environmental regulation solve pollution problems? Theoretical model and empirical research based on the skill premium. *Energy Econ* 94: 105068. https://doi.org/10.1016/j.eneco.2020.105068
Wang X, Sun C, Wang S, et al. (2018) Going green or going away? A spatial empirical examination of the relationship between environmental regulations, biased technological progress, and green total factor productivity. *Int J Environ Res Public Health* 15: 1917. https://doi.org/10.3390/ijerph15091917
Wang Y, Shen N (2016) Environmental regulation and environmental productivity: The case of China. *Renewable Sust Energy Rev* 62: 758766. https://doi.org/10.1016/j.rser.2016.05.048
Wang Y, Yan W, Ma D, et al. (2018) Carbon emissions and optimal scale of China's manufacturing agglomeration under heterogeneous environmental regulation. *J Clean Prod* 176: 140150. https://doi.org/10.1016/j.jclepro.2017.12.118
Wei Y, Liu X (2006) Productivity spillovers from R&D, exports and FDI in China's manufacturing sector. *J Int Bus Stud* 37: 544557. https://doi.org/10.1057/palgrave.jibs.8400209
Wu H, Hao Y, Ren S (2020a) How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. *Energy Econ* 91: 104880. https://doi.org/10.1016/j.eneco.2020.104880
Wu H, Xu L, Ren S, et al. (2020b) How do energy consumption and environmental regulation affect carbon emissions in China? New evidence from a dynamic threshold panel model. *Resour Policy* 67: 101678. https://doi.org/10.1016/j.resourpol.2020.101678
Wu H, Xue Y, Hao Y, et al. (2021) How does internet development affect energy-saving and emission reduction? Evidence from China. E*nergy Econ* 103: 105577. https://doi.org/10.1016/j.eneco.2021.105577
Xu X, Hou P, Liu Y (2022) The impact of heterogeneous environmental regulations on the technology innovation of urban green energy: a study based on the panel threshold model. *Green Financ* 1: 115136. https://doi.org/10.3934/GF.2022006
Yang J, Guo H, Liu B, et al. (2018) Environmental regulation and the Pollution Haven Hypothesis: do environmental regulation measures matter? *J Clean Prod* 202: 9931000. https://doi.org/10.1016/j.jclepro.2018.08.144
Yang X, Wang J, Cao J, et al. (2021b) The spatial spillover effect of urban sprawl and fiscal decentralization on air pollution: Evidence from 269 cities in China. *Empirical Econ* 63: 129. https://doi.org/10.1007/s00181-021-02151-y
Yang X, Wu H, Ren S, et al. (2021a) Does the development of the internet contribute to air pollution control in China? Mechanism discussion and empirical test. *Struct Change Econ Dyn* 56: 207224. https://doi.org/10.1016/j.strueco.2020.12.001
Yao Y, Hu D, Yang C, et al. (2021) The impact and mechanism of fintech on green total factor productivity. *Green Financ* 3: 198221. https://doi.org/10.3934/GF.2021011

Yu DH, Sun T (2017) Environmental regulation, skill premium and international competitiveness of manufacturing industry. *China Ind Econ* 5: 3553.

Yuan B, Xiang Q (2018) Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model. *J Clean Prod* 176: 895908. https://doi.org/10.1016/j.jclepro.2017.12.034

Zhang G, Liu W, Duan H (2020a) Environmental regulation policies, local government enforcement and pollution-intensive industry transfer in China. *Comput Ind Eng* 148: 106748. https://doi.org/10.1016/j.cie.2020.106748

Zhang H (2016) Exploring the impact of environmental regulation on economic growth, energy use, and CO2 emissions nexus in China. *Nat Hazards* 84: 213231. https://doi.org/10.1007/s11069-016-2417-7

Zhang K, Xu D, Li S (2019) The impact of environmental regulation on environmental pollution in China: An empirical study based on the synergistic effect of industrial agglomeration. *Environ sci pollut res* 26: 2577525788. https://doi.org/10.1007/s11356-019-05854-z

Zhang W, Li G, Uddin MK, et al. (2020b) Environmental regulation, foreign investment behavior, and carbon emissions for 30 provinces in China. *J Clean Prod* 248: 119208. https://doi.org/10.1016/j.jclepro.2019.119208

Zheng C, Deng F, Zhuo C, et al. (2022) Green Credit Policy, Institution Supply and Enterprise Green Innovation. *J Econ Anal* 1: 2851.

Zheng J, He J, Shao X, et al. (2022) The employment effects of environmental regulation: Evidence from eleventh five-year plan in China. *J Environ Manage* 316: 115197. https://doi.org/10.1016/j.jenvman.2022.115197

Zhou H, Qu S, Wu Z, et al. (2020) A study of environmental regulation, technological innovation, and energy consumption in China based on spatial econometric models and panel threshold models. *Environ Sci Pollut Res* 27: 3789437910. https://doi.org/10.1007/s11356-020-09793-y

Zhu S, He C, Liu Y (2014) Going green or going away: Environmental regulation, economic geography and firms' strategies in China's pollution-intensive industries. *Geoforum* 55: 5365. https://doi.org/10.1016/j.geoforum.2014.05.004