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Environmental regulation, green technology innovation, and industrial structure upgrading: The road to the green transformation of Chinese cities

Kerui Du [a], Yuanyuan Cheng [b], Xin Yao [b,*]

[a] School of Management, China Institute for Studies in Energy Policy, Collaborative Innovation Center for Energy Economics and Energy Policy, Xiamen University, Xiamen 361005, China
[b] China Center for Energy Economics Research, School of Economics, Xiamen University, Xiamen 361005, China

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ABSTRACT

Environmental regulation can facilitate the economy's green transformation through two channels: green technology innovation and industrial structure upgrading. However, the roles of economic development levels play on the effects of environmental regulation are usually ignored. In view of this, we estimate the heterogeneous impacts of environmental regulation on green technology innovation and industrial structure in 105 Chinese environmental monitoring cities through the partially linear functional-coefficient panel models. The new methodological framework can allow the variable, environmental regulation, to enter the model with coefficients being functions of economic development levels. Our results show that when the economic development levels are low, environmental regulation will restrain the development of green technology innovation but have insignificant impacts on the upgrading of industrial structure. With the growth of economic development levels, environmental regulation will show relatively weak impacts on green technology innovation and industrial structure. And when the economic development levels tend to be high, environmental regulation will significantly promote green technology innovation and industrial structure upgrading. Furthermore, we identify the mixed impacts of environmental regulation in different Chinese cities and put forward relevant policy recommendations for green transformation in China.

1. Introduction

The issues of massive energy consumption and serious environmental pollution have become increasingly prominent in China. In 2019, China was the most significant driver in global energy markets, whose primary energy consumption accounted for 24.3% of global consumption and more than 75% of net global growth (BP Statistical Review of World Energy, 2020). Besides, according to the 2020 Environmental Performance Index (EPI) results,[1] China still ranks 120th globally. Therefore, how to achieve coordinated development between economic growth and environmental protection is a problem that requires urgent attention from the Chinese government. And environmental regulation (ER) is one of the essential ways to realize the green transformation of the economy.

Many previous studies have verified the advantageous roles of ER in the fields of energy and environment, such as the green efficiency promotion (Galloway and Johnson, 2016; Curtis and Lee, 2019; Wang et al., 2019; Su and Zhang, 2020), the energy consumption saving (Liu et al., 2018), the carbon emission reduction (Wang and Wei, 2020; Zhao et al., 2020a; Zhao et al., 2020b), the SO_2 emission reduction (Pang et al., 2019), and the haze pollution decrease (Zhou et al., 2019; Zhang et al., 2020c). However, some scholars believe that ER will raise the costs of pollution prevention and control as well as production, because it requires companies to reduce pollutant emissions and achieve cleaner production. Hence, ER is not conducive to promoting the companies' production capacity and competitiveness (Gollop and Roberts, 1983; Grey and Shadbegian, 2003; Ambec et al., 2013; Li et al., 2019b). Another contrary view was put forward by Porter (1991). The Porter Hypothesis claims that proper ER can attract the enterprises' innovation activities and prompt enterprises to reduce the production inputs and costs. That is to say, ER can improve firms' productivity due to innovation activities, which can increase profitability and offset the increased costs of environmental governance.

The beneficial effects of ER on promoting the green transformation of the economy mainly come from two channels: green technology innovation and industrial structure upgrading. From the perspective of green technological innovation, it helps reduce pollution emissions from fossil energy and increase the use of clean energy. Although

* Corresponding author.
E-mail address: lyhneyao@sina.com (X. Yao).

[1] The 2020 EPI Results could be found at https://epi.yale.edu/epi-results/2020/component/epi

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green technology innovation will increase the R&D expenditure of firms, it also facilitates boosting firms' productivity and effectively controlling the discharge of wastewater, waste gas, and solid waste in the production. Promoting technological innovation of enterprises through strict environmental policies can achieve an effective reduction of environmental pollution under the premise of ensuring enterprises' production (Ouyang et al., 2020a). From the perspective of industrial structure, pollution-intensive industries always consume too many resources and produce a lot of environmental pollutants. If no external compulsory environmental policy is imposed, companies would not consider environmental pollution during production (Greenstone and Hanna, 2014), which means that the environmental costs are often ignored. Therefore, the deviation between the enterprises' private costs and the total costs of society will lead to overproduction in the pollution-intensive industries. Through the implementation of ER, enterprises will be asked to consider the external costs caused by environmental pollution in the production, thereby compelling pollution-intensive enterprises to reduce production. In addition, strict ER can also promote the vigorous development of emerging environmentally-friendly industries and lead to the industrial structure transformation.

Moreover, the impacts of ER on green technology innovation and industrial structure upgrading may show heterogeneities in different regions due to the constraints of the economic development levels. Specifically, regions with low economic development levels only have limited resources, while green technological innovation requires a large number of resource inputs. Therefore, regions with low economic development levels are more challenging to carry out innovative R&D. On the contrary, for regions with higher economic development levels, more funds and talents can contribute to the R&D activities. In addition, ER will also affect the production of enterprises. For regions with low economic development levels, industrial competitiveness is relatively weak. Therefore, these regions are more likely to be squeezed out of production by ER. And regions with low economic development levels need to rely on the secondary industry to drive the economy's growth, which is not conducive to the development of clean industries. Fig. 1 depicts the evolution of the distribution of the logarithm of real GDP per capita in different Chinese cities. It can be seen from Fig. 1 that although there are remarkable GDP gaps across various cities, the economic development levels of Chinese cities have been continuously improving. Therefore, the roles of ER play on green technology innovation and industrial structure may also change. Considering different economic development levels, we aim to analyze the specific impacts of ER on green technology innovation and industrial structure upgrading for Chinese cities in this paper.

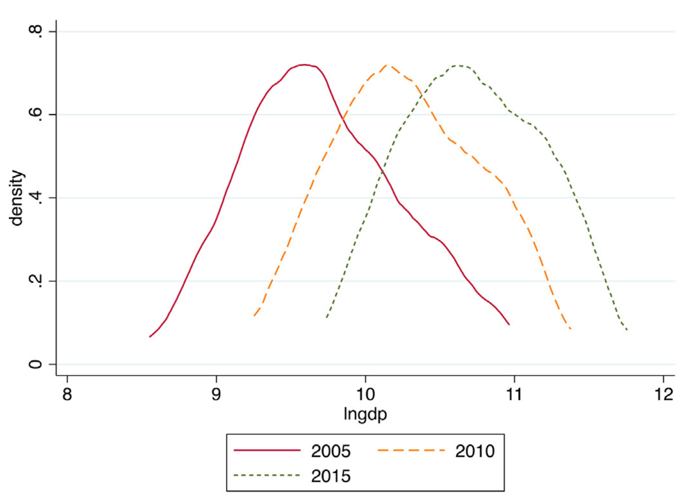

Fig. 1. Kernel density evolution of lnGDP in 105 Chinese cities.

The main contributions of this study are summarized as follows. First, we comprehensively analyze the impacts of ER on the green transformation of 105 Chinese environmental monitoring cities and measure the effects from two channels: green technology innovation and industrial structure upgrading. This helps us to understand the roles of ER from a clearer and comprehensive perspective. Second, we test the hypothesis that if the advantageous impacts of ER on the green transformation will be conditional on economic development levels. We identify the heterogeneous effects of ER on different types of cities and fill the relevant research gap. Third, we employ a new methodological framework, i.e., partially linear functional-coefficient panel model, to specify the non-linear relationship between ER and green transformation. This model can help prevent model misspecification and obtain the functional coefficients of ER on green technology innovation and industrial structure, thereby getting more accurate estimating results about the impacts of ER.

The rest of this paper is organized as follows. In Section 2, we outline relevant literature on ER and its relationship with technological innovation and industrial structure. In Section 3, we mainly introduce the models and related variables used in this study. Section 4 is about the empirical results and discussion. And Section 5 is the conclusion and policy recommendations.

2. Literature review

2.1. Environmental regulation and technology innovation

The conclusions about how ER affects technological innovation are dissimilar in different researches. Porter and van der Linde (1995a, 1995b) propose that ER will first inhibit technological innovation development, and only after a certain period will it begin to promote technological innovation. The work of Ouyang et al. (2020a) proves the above opinion and shows that the specific impacts of ER on technological innovation in the industrial sectors are U-shaped. Specifically, there are offsetting effects in the short term, but the effects tend to be compensatory in the long run. Yuan et al. (2017) find that the effects of ER on technical innovation are inverted U-shaped in the manufacturing industries with high and low eco-efficiency, but U-shaped in the manufacturing industries with medium eco-efficiency.

Many scholars believe that ER can directly stimulate innovation activities. For example, Brunnermeier and Cohen (2003) show that the increasing expenditure on pollution abatement will lead to a larger number of environmental innovations, and industries with international competitiveness are more likely to have environmental innovation capabilities. Using the expense of pollution abatement and control as the representative for ER, Rubashkina et al. (2015) produce obvious evidence for the promoting role of ER on R&D activity. Taking the certification of ISO 14000 as a voluntary ER, Bu et al. (2020) claim that voluntary ER will promote the Chinese firms' innovation, and the Porter Hypothesis is further discussed. Turken et al. (2020) discuss green technology and the decisions to reduce emissions at the end of the pipeline under different types of ER, and the outcomes show that if ER has been implemented, firms should focus on the investment of green technology emissions reduction. Hille et al. (2020) use different renewable energy support policies to distinguish the design and intensity of ER and find that the impacts on the innovation could increase significantly as time goes on. Besides, Herman and Xiang (2019) show that ER measured with foreign environmental policies will also exhibit induced effects on domestic clean technologies.

However, some scholars think that ER can enter into force only under certain conditions. For example, through the spatial Durbin model, Feng et al. (2019) find that only the cooperation effects of ER and FDI will promote the innovation ability of Chinese cities, and the relevant results support the Porter Hypothesis. From the perspectives of industry and region, Jiang et al. (2018) define two types of ER and find that industrial regulation plays a negative role on innovation performance, while regional regulation can stimulate firms' innovation performance. Song et al. (2018) verify that the beneficial effect of staff quality on green technology is limited under the loose ER policy. Only with the implementation of strict ER, the firms will seek to improve the staff quality and further pursue green innovation. Fu and Jian (2021) claim that stricter ER can stimulate corporate innovation in China only when interacted with areas with high levels of corruption, which means that bribery expenditure is an important channel to ensure the effectiveness of ER in developing countries. Borsatto and Amui (2019) state that the relationship between ER and green innovation is inconsistent. Specifically, there are significant impacts of ER on green innovation when green innovation is measured with UN Global Compact and environmental investments. But the effects are insignificant when green innovation is measured with some other indicators.

2.2. Environmental regulation and industries

Previous studies have also discussed whether ER can promote the transformation and upgrading of industries, and the roles of ER on the productivity and competitiveness of the firms are analyzed. Through constructing quantitative indices of policy objectives and measures, Zhang et al. (2019) explore the specific influences of ER on industrial structure from the aspects of spatial and time-lag effects and find that industrial structure upgrading will benefit from ER in the long-term. From the perspective of the industry chain, Zhu et al. (2019) investigate the diverse impacts of ER on the steel industry and clarify that the steel industry's production will increase with the implementation of strict ER. Ju et al. (2020) analyze the differentiated effects of three different classes of ER (mandatory control, market incentive, and voluntary compliance) on the green total factor productivity of various industries (heavy-polluting, middle-polluting, and low-polluting). It is found that different kinds of ER will show heterogeneous impacts on the same industry, and the energy-saving and emission reduction potential of middle-polluting industries is relatively large. Zhai and An (2020) find that the positive effects of ER on the green transformation of the manufacturing industry come into effect through some other factors such as financing capacity and governmental behavior. Taking the mandatory emission trading scheme (ETS) in energy-intensive industries as the implementation of ER, Ouyang et al. (2020b) show that ER is effective in reducing the carbon emission of heavy industries, and some suggestions of optimizing industrial structure are further proposed. Liu et al. (2017) claim that the impacts of wastewater discharge standards on the labor demand of textile printing and dyeing industries are heterogeneous. Specifically, the effects on domestically-owned private enterprises are far more significant than the impact on state-owned or foreign-owned enterprises. However, focusing on the impact of labor costs and ER on the structure of the manufacturing industry, the study of Zheng et al. (2019) shows that the benefits from ER are not enough to offset the costs brought by the stringent regulation, that is, the number of competitive companies will decrease. And El-Zayat et al. (2006) find that although industries in Egypt have positive attitudes towards environmental laws and regulations, these industries have not fully complied with ER due to social and economic reasons.

Some researchers have also expressed concern about whether ER can lead to industrial redistribution, that is to say, whether the Pollution Haven Effect exists. Mulatu et al. (2010) estimate the effects of ER on the location of 16 manufacturing industries in 13 European countries and verify the presence of the Pollution Haven Effect. Based on the EU Air Quality Framework Directive, Bagayev and Lochard (2017) measure the regulation stringency of air quality in the EU and find that EU countries with more stringent air pollution regulations are more inclined to import polluting products from developing countries than to produce by themselves. Wu et al. (2019) examine the critical role of ER in the redistribution of pollution-intensive industries. The results prove the co-existence of the Pollution Haven Hypothesis and the Porter Hypothesis in the Chinese industries, and show that different industrial characteristics act dissimilarly to the changes in ER. Zhao et al. (2020b) show that stringent ER will not only directly affect carbon dioxide reduction but also indirectly affect investment in carbon-intensive industries, leading to the transfer of carbon-intensive industries within regions. Taking agglomeration economies and transport costs as the proxy of industrial immobility, Cole et al. (2010) show that the effects of ER on net imports will be lower in the industries with higher levels of immobility. Moreover, Shen et al. (2017) find that the formation of the new pollution haven can be avoided by the targeted ER such as constructing sewage treatment plants.

2.3. Innovation of this study

Most previous studies related to ER only focused on one channel of green transformation: green technological innovation or industrial structure. In this paper, we measure the impacts of ER from the two channels simultaneously and distinguish the differences in the effects on green technological innovation and industrial structure. The research that focuses on ER in China at the city-level is limited, and the heterogeneous effects caused by different levels of economic development have also been ignored. In this paper, we analyze the impacts of ER and take the influence of various economic development levels into consideration, thus providing specific policy suggestions for Chinese cities' green transformation.

3. Econometric models, variables, and data

3.1. Econometric models

To study the impacts of ER on green technological innovation and industrial structure, we first consider the linear model shown in Eq. (1).

$$Y_{it} = \gamma Z_{it-1} + \beta' X_{it-1} + \delta_i + \mu_{it} \tag{1}$$

Where, Z_{it-1} represents the level of ER for the i-th city at time $t-1$. To fully consider the time required from implementation to entering into force, the key explanatory variable, ER, is lagged by one period. Y_{it} includes two explained variables which are green technology innovation (*lnGTI*) and industrial structure (*lnIS*) in our study, respectively. X_{it-1} is a vector of control variables that includes financial support to technology and education (*lnRD*), city size (*lnPOP*), human capital level (*lnHC*), investment in fixed assets (*lnINV*), and economic openness level (*lnFDI*). All control variables are also lagged by one period to avoid being affected by the explanatory variable at time $t-1$ and making the empirical results biased. δ_i denotes the unobserved individual heterogeneity and μ_{it} is the random error that is assumed to be *i. i. d* $(0,\sigma_\mu^2)$.

As discussed in Section 1, the impacts of ER on the green transformation of China's cities may be affected by the economic development levels. To examine the relationship between the roles of ER and economic development, we further take the economic development levels U_{it-1} into account in our model. Traditionally, researchers may consider constructing the interaction term between ER and economic development levels based on Eq. (1) to investigate the influence of economic development levels. The model with interaction term is shown in Eq. (2).

$$Y_{it} = \gamma_1 Z_{it-1} + \gamma_2 Z_{it-1} \times U_{it-1} + \beta' X_{it-1} + \delta_i + \mu_{it} \tag{2}$$

And the specific impacts of ER on the green transformation of China's cities can be calculated as $\gamma_1 + \gamma_2 U_{it-1}$. However, this strategy is likely to lead to model misspecification and biased estimation results due to a priori judgment on the rationality of the construction of interaction term and rigorous assumptions imposed on the regression equation (see Li et al., 2019a; Du et al., 2020a; Du et al., 2020b for details). Therefore, to overcome the weaknesses brought by the method of constructing

Table 1
Five indicators of environmental regulation.

Indicator	Description	Unit	Weight
WasWater_OperCost_Ratio	Industrial waste water treatment facility operating costs/Nominal GDP	%	0.1963
WasWater_EmisInten_Inverse	Real GDP/Industrial waste water discharge	billion yuan/million tons	0.1968
WasGas_OperCost_Ratio	Industrial waste gas treatment facility operating costs/Nominal GDP	%	0.2624
WasGas_EmisInten_Inverse	Real GDP/Industrial waste gas emissions	billion yuan/100 million cubic meters	0.3120
SolWaste_CompreUtil_Ratio	Comprehensive utilization rate of industrial solid waste	%	0.0324

interaction term, we let Z_{it-1} enter the model with coefficients being functions of U_{it-1}. Then we have:

$$Y_{it} = \gamma(U_{it-1})Z_{it-1} + \beta' X_{it-1} + \delta_i + \mu_{it} \tag{3}$$

Eq. (3) is a partially linear varying coefficient panel data model, and the heterogeneous impacts of ER on the green transformation of Chinese cities under different economic development levels can be expressed as the functional coefficient $\gamma(U_{it-1})$. Based on the nonparametric kernel method, Li et al. (2002) analyze a cross-sectional model with coefficients being nonparametric functions and without the linear component. An et al. (2016) further extend the model of Li et al. (2002) to a partially linear varying coefficient panel data model with fixed effects and attempt to estimate this model with the series method. The specific estimation procedure of An et al. (2016) is as follows.

Step 1. Taking first-time difference.

$$\Delta Y_{it} = \Delta(\gamma(U_{it-1})Z_{it-1}) + \beta' \Delta X_{it-1} + \Delta\mu_{it} \tag{4}$$

Then, the fixed effects δ_i in Eq. (3) has been eliminated.

Step 2. Approximating the varying coefficient function $\gamma(U_{it-1})$ by a linear combination of k base functions:

$$p(U_{it-1})'\theta = [p_1(U_{it-1}), \ldots, p_k(U_{it-1})] \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_k \end{bmatrix} \tag{5}$$

Where, $p(U_{it-1})$ is a $k \times 1$ vector of base functions, and θ is a $k \times 1$ vector of unknown parameters. When k grows large, there exists a linear combination of $p_i(U_{it-1})$ which can approximate any smooth function $\gamma(U_{it-1})$ well, and the approximation MSE will be small as possible. Then, Eq. (4) can be rewritten as:

$$\Delta Y_{it} = \Delta(Z_{it-1}p(U_{it-1}))'\theta + \beta' \Delta X_{it-1} + \Delta\varepsilon_{it} \tag{6}$$

Where $\Delta\varepsilon_{it} = \Delta\mu_{it} + \Delta(\gamma(U_{it-1})Z_{it-1}) - \Delta(Z_{it-1}p(U_{it-1}))'\theta$, which denotes the series approximation error.

Step 3. Calculating the least-square estimators.

$$\left(\widehat{\beta}', \widehat{\theta}'\right) = \left[\Delta\widetilde{X}' \Delta\widetilde{X}\right]^{-1} \Delta\widetilde{X}' \Delta\widetilde{Y} \tag{7}$$

Where, $\Delta\widetilde{Y} = \begin{bmatrix} \Delta Y_{12} \\ \vdots \\ \Delta Y_{NT} \end{bmatrix}$, and $\Delta\widetilde{X} = \begin{bmatrix} \Delta X'_{11}, \Delta(Z_{11}p(U_{11})) \\ \vdots \\ \Delta X'_{N(T-1)}, \Delta(Z_{N(T-1)}p(U_{N(T-1)})) \end{bmatrix}$.

What's more, the coefficient function $\gamma(\cdot)$ can be estimated as:

$$\widehat{\gamma}(U_{it-1}) = p(U_{it-1})'\widehat{\theta} \tag{8}$$

Therefore, based on the study of An et al. (2016), we are going to estimate the following models:

$$\begin{aligned} \ln GTI_{it} = {} & \gamma(\ln GDP_{it-1})ER_{it-1} + \beta_1 \ln RD_{it-1} + \beta_2 \ln POP_{it-1} \\ & + \beta_3 \ln HC_{it-1} + \beta_4 \ln INV_{it-1} + \beta_5 \ln FDI_{it-1} + \delta_i + \mu_{it} \end{aligned} \tag{9}$$

$$\begin{aligned} \ln IS_{it} = {} & \gamma(\ln GDP_{it-1})ER_{it-1} + \beta_1 \ln RD_{it-1} + \beta_2 \ln POP_{it-1} \\ & + \beta_3 \ln HC_{it-1} + \beta_4 \ln INV_{it-1} + \beta_5 \ln FDI_{it-1} + \delta_i + \mu_{it} \end{aligned} \tag{10}$$

Where, $\gamma(lnGDP_{it-1})$ is the functional coefficients of ER_{it-1}. Du et al. (2020c) develop a Stata package for the estimation of partially linear functional-coefficient panel models.

3.2. Variables and data

3.2.1. Explanatory variable

The key explanatory variable in our study is ER. It is challenging to measure ER with a single index (Liao and Shi, 2018). Considering the availability of data at the city-level, we choose five indicators (see the first column in Table 1) to represent the levels of ER. These five indicators reflect the levels of cities' environmental governance from three perspectives: industrial wastewater, industrial waste gas, and industrial solid waste, which are considered in most researches related to ER (Zhao and Sun, 2016; Ren et al., 2018; Liu et al., 2021). The raw data comes from China Environment Yearbook. We first handle the raw data (see the second column in Table 1) so that the price impacts can be eliminated. And the directions of the effects reflected by these five indicators are consistent (the larger the value, the higher the level of environmental governance). We then use the entropy weight method, which is widely applied in the comprehensive evaluation, to synthesize one index as a proxy variable for ER. The basic idea of the entropy weight method is that the more useful information a specific indicator provides, the higher the weight it will get (Huang et al., 2018; Liu et al., 2019; Yuan et al., 2019). From Table 1 we can find that the weights of these five indicators are relatively balanced. Therefore, the synthetic index we constructed can reflect the levels of ER from the whole perspective of industrial wastewater, industrial waste gas, and industrial solid waste. The specific calculation process of the entropy weight method is as follows.

Step 1. Standardize the original value.

$$X^*_{ij} = \frac{X_{ij} - \min(X_{\cdot j})}{\max(X_{\cdot j}) - \min(X_{\cdot j})} \tag{11}$$

Where, X_{ij} is the original value of city p at time q, ($pq = i = 1, 2, \ldots, m$) with indicator j ($j = 1, 2, \ldots, n$). And $\max(X_{\cdot j})$ and $\min(X_{\cdot j})$ are the largest and smallest value in indicator j, respectively. After standardization, the influences of different dimensions will be eliminated.

Step 2. Calculate the contribution degree of each standardized value.

$$Y_{ij} = \frac{X^*_{ij}}{\sum_{i=1}^{m} X^*_{ij}} \tag{12}$$

Step 3. Calculate the entropy of each indicator.

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} Y_{ij} \cdot \ln Y_{ij} \tag{13}$$

The particular value ($Y_{ij} = 0$) in indicator j will be excluded because $\lim_{z \to 0} z \cdot \ln z = 0$.

Step 4. Calculate the divergence coefficient.

$$d_j = 1 - e_j \tag{14}$$

Therefore, the indicator j plays a more critical role if d_j is larger.

Step 5. Define the weight of each indicator.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{15}$$

Step 6. Determine the level of ER for each city at different times.

$$ER_i = \sum_{j=1}^{n} w_j \cdot x_{ij}^* \tag{16}$$

3.2.2. Explained variables

We use the number of green technology patents as a proxy variable for the level of green technology innovation (GTI). The green technology patent classification codes come from the "IPC Green Inventory" guideline[2] developed by the IPC Committee. There are seven topics in the "IPC Green Inventory", and the environmentally sound technologies under these different topics are listed by the United Nations Framework Convention on Climate Change (UNFCCC). We collect the data of China's green technology patents at the city-level on the Patent Search and Analysis System (PSS-System) of the China National Intellectual Property Administration (CNIPA). We only focus on the authorized patents and sort them by the application date because we want to analyze the incentives of ER for green technology innovation application.

Another work we want to do is to figure out the impacts of ER on industrial structure (IS). We use the ratio of the added value of the tertiary industry to that of the secondary industry as the proxy variable for industrial upgrading because the development of the tertiary industry reflects clean and green production (Wang et al., 2018; Zhou et al., 2019). The relevant data are collected from the CEIC database.

3.2.3. Control variables

In the study, we choose control variables from five aspects: financial support to technology and education, city size, human capital level, investment in fixed assets, and economic openness. The ratio of fiscal expenditures of technology and education to GDP is used to represent the level of financial support to technology and education (RD). The size of a city is measured by the number of people (POP). We show the level of human capital in a city by the number of high school students (HC). The ratio of fixed-asset investment to GDP is used to measure the level of investment in fixed assets (INV). And the ratio of FDI to GDP is represented as the economic openness (FDI). Relevant data come from CEIC, except for RD, which is collected from China City Statistical Yearbook. The reasons for choosing these control variables are as follows. Innovative R&D activities require financial support and human capital investment because the cost of R&D activities is relatively high, and a higher knowledge level is conducive to improving the ability of learning and innovation (Song et al., 2018). And financial support and human capital investment also help promote the development of high-tech industries. Therefore, financial support to technology and education and human capital level are chosen. The pollution haven hypothesis supposes that more FDI will lead to the transfer of pollution-intensive industries to the host country. And the pollution halo hypothesis proposes that FDI will promote technological spillover effects within regions (Zhao et al., 2020b). So economic openness level is chosen. In addition, the optimization of the investment structure is essential to achieve green development (Xie et al., 2021). So investment in fixed assets is chosen. And we further control the impacts of city size.

To investigate whether the impacts of ER on green technology innovation and industrial structure are heterogeneous under different levels of economic development, we use real GDP per capita to represent the economic development level (GDP). Due to data availability, we mainly focus on the 105 Chinese environmental monitoring cities in this study. The period of the two explained variables is 2003–2016, and the period of other variables is 2002–2015. All the nominal variables have been deflated into the 2001 constant prices. The descriptive statistics of all variables are presented in Table 2.

[2] It can be found on the website of the World Intellectual Property Organization (WIPO), https://www.wipo.int/classifications/ipc/green-inventory/home.

Table 2
Descriptive statistics.

Variable	N	Mean	SD	Min	Max	Unit
lnGTI	1470	4.322	1.888	0.000	9.526	Piece
lnIS	1470	−0.216	0.475	−2.362	1.562	\
ER	1470	0.083	0.041	0.024	0.447	\
lnGDP	1470	10.088	0.671	8.116	11.757	Yuan
lnRD	1470	−0.059	0.612	−1.843	1.653	%
lnPOP	1470	6.105	0.719	3.306	8.008	Ten thousand people
lnHC	1470	4.286	1.363	−0.268	6.950	Thousand people
lnINV	1470	3.953	0.417	2.464	5.096	%
lnFDI	1470	0.474	1.189	−6.010	3.001	%

Table 3
Estimation results of fixed effect panel models.

	lnGTI	*lnIS*
ER	3.280^{***}	1.454^{***}
	(1.132)	(0.485)
lnRD	0.961^{***}	0.052
	(0.151)	(0.039)
lnPOP	2.233^{***}	0.400^{***}
	(0.347)	(0.148)
lnHC	0.766^{***}	−0.030
	(0.145)	(0.040)
lnINV	0.847^{***}	−0.038
	(0.136)	(0.042)
lnFDI	-0.110^{***}	−0.005
	(0.041)	(0.015)
Constant	-16.101^{***}	-2.497^{***}
	(2.222)	(0.896)
N	1470	1470
R^2	0.787	0.117

Note: Cluster robust standard errors in parentheses. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$.

4. Empirical study

4.1. First look: estimation results of linear panel models

The estimation results of the linear model in Eq. (1) are shown in Table 3. The estimated coefficients of *ER* on *lnGTI* and *lnIS* are both positive and significant, which indicates that GTI and IS will increase 3.280% and 1.454% respectively, if the value of *ER* increases 0.01. These results preliminarily prove that ER can help promote the green transformation of Chinese cities. On the one hand, ER can promote green innovation and stimulate the application of green technology. On the other hand, ER can promote the transformation of industrial structure and make the proportion of the tertiary industry increase. As for the control variables, it seems that the control variables at the last period have more significant impacts on *lnGTI* than on *lnIS*. Table 3 mainly shows the impacts of ER on green transformation without considering the regional economic development levels. In the next section, we will begin to discuss the heterogeneous impacts of ER on the green transformation of Chinese cities under different economic development levels.

Table 4
Estimated results of the linear part of partially linear functional-coefficient panel models.

	lnGTI	lnIS
lnRD	0.089*	−0.011
	(0.051)	(0.009)
lnPOP	1.636***	−0.052
	(0.240)	(0.045)
lnHC	0.218***	−0.014
	(0.074)	(0.015)
lnINV	0.391***	−0.095***
	(0.079)	(0.016)
lnFDI	0.015	0.011***
	(0.019)	(0.004)
N	1365	1365
R^2	0.175	0.097

Note: Bootstrap standard errors in parentheses. The number of replications used is 1000 times. ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

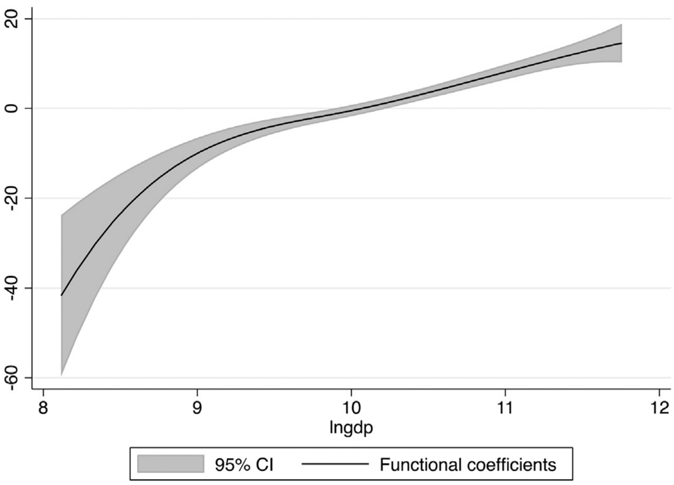

Fig. 2. Functional coefficients of ER with respect to GTI.

4.2. Estimation results of partially linear functional-coefficient panel models

In this section, we analyze the influences of ER on green technology innovation and industrial structure based on the partially linear functional-coefficient panel models. The estimated parameters of the linear part in Eqs. (9) and (10) are presented in Table 4. The heterogeneous effects of ER under different economic development levels are displayed in Figs. 2 and 3. From Fig. 2, we can find that the curve is relatively flat when *lnGDP* lies around 10. Fig. 3 shows that the curve is flat when *lnGDP* is lower than 10. The 95% confidence interval indicates that the impacts of ER at these intervals are not or slightly significant. Besides, Figs. 2 and 3 also examine that the effects of ER on green technology innovation and industrial structure will vary with different economic development levels.

For green technology innovation, the implementation of ER has suppressive effects when the economic development is at relatively low levels, which means that it is not good for the development of green innovation. With the growth of the economic level, the inhibitory effects will gradually decrease. When the economy develops to a higher level, ER will begin to exhibit beneficial impacts on green technology innovation. Some reasons can be used to explain the above results. In the regions with low economic development levels, ER will raise the production costs as well as weaken the competitiveness of enterprises. And the increased production costs will prevent companies from investing in R&D activities. Moreover, innovation capabilities are weak in these regions, so it isn't easy to achieve energy-saving and emission-reduction through technological innovation. Therefore, ER

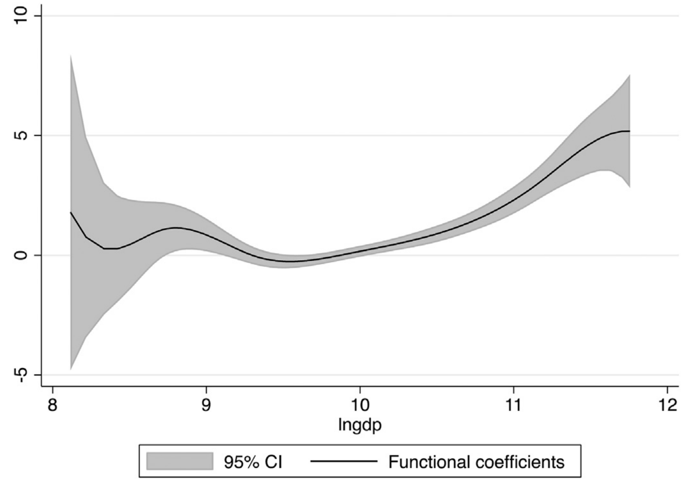

Fig. 3. Functional coefficients of ER with respect to IS.

shows inhibitory effects in the regions with low economic development levels. But in the regions with higher levels of economic development, R&D foundation and innovation capabilities are more potent, so strict ER can inspire companies to attain environmental protection through green technology innovation.

For the industrial structure, ER exhibits promoting effects on the industrial structure upgrading, but the effects are also dissimilar at different economic development levels. Specifically, ER can facilitate the progress of the clean industry more effectively at higher levels of economic development. For regions with lower economic development levels, the effects of ER seem to be insignificant. The reasons are as follows. In the stage of low economic development, the government will pursue the goal of economic growth, and the secondary industry primarily dominates the economic structure. The goal of economic development is more important than the pursuit of better environmental quality. Therefore, the impacts of ER on industrial structure optimization will be weakened because the second industry plays a considerable role in promoting economic growth. But when the economic development has risen to a higher level, the pressure for better environmental quality also increases. Therefore, strict ER can stimulate the industrial transformation from the secondary industry to the tertiary industry, and the industrial structure optimization effects of ER will gradually strengthen.

4.3. Specific results of Chinese cities

In this section, we paint a more comprehensive picture to illustrate the heterogeneous effects of ER on the green transformation of different types of Chinese cities. To this end, we take the average value of the real GDP per capita from 2002 to 2015 as the standard and divide 105 cities into three groups: regions with low economic development levels, regions with medium economic development levels, and regions with high economic development levels. The impacts of ER on green technology innovation and industrial structure for all cities in 2005, 2010, and 2015 are presented in Fig. 4a–c, respectively.

It can be seen from Fig. 4a that in 2005, for several cities that belong to the regions with low economic development levels, both green technological innovation and industrial structure can be influenced by ER significantly. Specifically, ER can promote the upgrading of the industrial structure, but it will inhibit the development of green technology innovation. Besides, for most cities in regions with low economic development levels, the impacts of ER on the industrial structure are insignificant. In 2005, the ER of most cities with medium levels of economic development had negligible effects on the industrial structure, and it does not contribute to green technology innovation. And ER of the

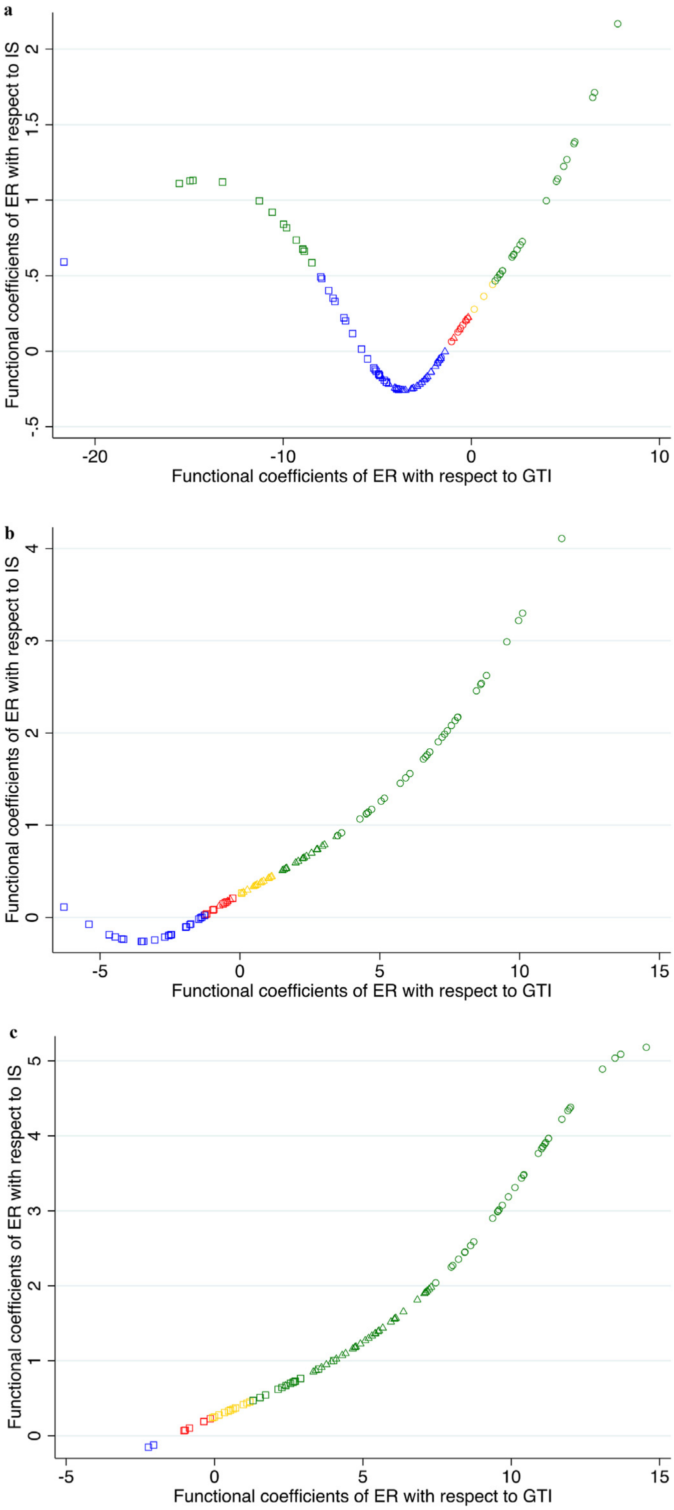

Fig. 4. (a) Functional coefficients of ER in 2005. (b) Functional coefficients of ER in 2010. (c) Functional coefficients of ER in 2015. Note: *Square* means that the real GDP per capita is at a low level; *Triangle* means that the real GDP per capita is at a medium level; *Circle* means that the real GDP per capita is at a high level. *Red* means that the impacts of ER on lnGTI and lnIS are both insignificant; *Yellow* means that ER has significant impacts on lnIS, but has insignificant impacts on lnGTI; *Blue* means that ER has significant impacts on lnGTI, but has insignificant impacts on lnIS; *Green* means that the impacts of ER on lnGTI and lnIS are both significant.

remaining cities that belong to the regions with medium levels of economic development has insignificant impacts on both green technological innovation and industrial structure. For most cities in regions with high economic development levels, ER can significantly facilitate the development of both green technological innovation and industrial structure.

From Fig. 4b we can find that in 2010, for cities at regions with low economic development levels, the restraining impacts of ER on green technological innovation have been reduced. Similarly, for cities that belong to the regions with medium economic development levels, ER no longer restricts the development of green technological innovation. And the positive roles of ER on the industrial structure have begun to exhibit. For cities in regions with high levels of economic development, the beneficial effects of ER on promoting green technological innovation and industrial structure have been strengthened.

Moreover, from Fig. 4c we can see that in 2015, ER of all cities that belong to the regions with high and medium levels of economic development can significantly promote the development of green technology innovation and industrial structure. For cities in regions with low economic development levels, the restraining impacts of ER on green technological innovation have been further cut down. And the stimulation of ER on the upgrading of the industrial structure has been strengthened.

Fig. 4a–c tell us an interesting story that, as time goes on, the negative impacts of ER have gradually disappeared, and the positive effects of ER on the green transformation have become more and more prominent. As shown in Fig. 1 that the economic development levels of Chinese cities have been continually improving from 2005 to 2015. Therefore, we verify the hypothesis that the impacts of ER on the green transformation of Chinese cities are affected by economic development levels. A higher level of economic development is conducive to ER to play a positive role in green technology innovation and industrial structure. And the above facts have also proved that ER can guide the green development of Chinese cities through two channels: green technology innovation and industrial structure upgrading in recent years.

4.4. Robustness analysis

To examine the robustness of the empirical results, we replace the two explained variables GTI and IS. Specifically, we use the knowledge stock of green technology innovation to represent the output of green innovation. Based on GTI, the knowledge stock of green technology innovation (GTIS) can be calculated by the perpetual inventory method, which is expressed in Eq. (17).

$$GTIS_t = GTI_t + (1-\delta)\cdot GTIS_{t-1} \tag{17}$$

where $GTIS_{t-1}$ denotes the knowledge stock of green technology innovation in the last period. When we calculate the knowledge stock of green technology innovation at time t, we should consider the depreciation of the knowledge stock before. According to the existing literature (Bottazzi and Peri, 2007; Verdolini and Galeotti, 2011; Yan et al., 2017), the depreciation rate δ is set to be 10%. Because the data collection of patents in China began in 1985, the initial number of green technology innovation GTI_0 is the number of green technology patents in 1985 (Lin and Chen, 2019; Cheng and Yao, 2021). Besides, we use the ratio of the added value of the tertiary industry to GDP (ISR) to reflect changes in the industrial structure. The estimation results of the linear part are shown in Table 5, and the functional coefficients of GTIS and ISR are displayed in Figs. 5 and 6.

From Table 5, we can find that the robustness results are consistent with the empirical results in Table 4. Moreover, from Fig. 5 we can find that, as the economic development levels change, the impacts of *ER* on *lnGTIS* are significantly negative initially, then becoming insignificant, and finally are significantly positive. And from Fig. 6, the functional coefficients of *ER* with respect to *lnISR* are insignificant at first, then becoming significantly positive. Therefore, we claim that our empirical results are robust.

Table 5
Robustness results of the linear part of partially linear functional-coefficient panel models.

	lnGTIS	lnISR
lnRD	0.141***	−0.004
	(0.017)	(0.006)
lnPOP	1.338***	0.021
	(0.095)	(0.028)
lnHC	0.220***	−0.006
	(0.025)	(0.009)
lnINV	0.350***	−0.055***
	(0.032)	(0.010)
lnFDI	−0.010	0.009***
	(0.007)	(0.003)
N	1365	1365
R^2	0.496	0.074

Note: Bootstrap standard errors in parentheses. The number of replications used is 1000 times. ***p < 0.01. **p < 0.05. *p < 0.1.

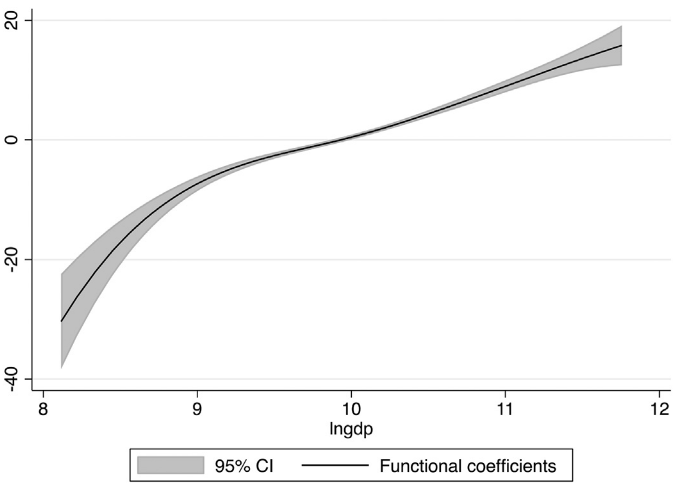

Fig. 5. Functional coefficients of ER with respect to GTIS.

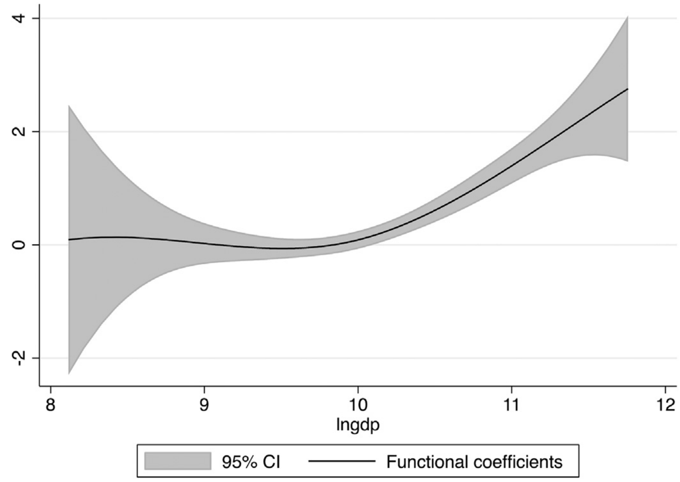

Fig. 6. Functional coefficients of ER with respect to ISR.

5. Conclusions and policy implications

Green technology innovation and industrial structure upgrading are two essential channels to achieve green transformation. And ER is a crucial measure to prevent and control pollution as well as achieve the goal of sustainable economic development. This paper mainly studies the heterogeneous impacts of urban ER on green technology innovation and industrial structure, taking the roles of economic development levels into account. The partially linear functional-coefficient panel model is used to prevent model misspecification. The functional marginal effects of ER on the green technology innovation and industrial structure under different economic development levels are obtained.

The main conclusions are as follows. First, with the growth of the economic development levels, the impacts of ER on green technology innovation are significantly negative at first. The negative effects are slowly reduced to be insignificant, and finally, ER performs increasingly positive roles on green technology innovation. Second, the effects of ER on the industrial structure also change with the economic development levels. Specifically, the promotion effects of ER on industrial structure upgrading are insignificant at low economic development levels and then progressively increase. Third, as time goes on, the roles of ER in promoting the green transformation of Chinese cities are more and more prominent. Taking the impacts of ER in 2005, 2010, and 2015 as examples, this paper reveals that in 2005, only a few cities that belong to the regions with high economic development levels can significantly promote the development of green technology innovation and industrial structure through the implementation of ER. By 2010, the implementation of ER is good for the green transformation of all cities with high economic development levels and several cities with medium economic development levels. In 2015, only in a small number of cities that belong to the regions with low economic development levels, the beneficial impacts of ER had not been visible.

The empirical results show that ER will perform completely dissimilar impacts on green technology innovation and industrial structure under different economic development levels. Therefore, environmental policies should be compatible with regional economic development. At the same time, relevant supporting policies should be promulgated to cooperate with the implementation of ER. Given the differences in regional economic development levels, technological innovation, energy conservation, and emission reduction of industries should be actively guided (Zhu and Lin, 2020; Song et al., 2020). Considering the differences in different regions is also vital to achieving the dual goals of economic development and environmental protection (Lin and Zhu, 2020). According to the main findings of this study, the relevant policy recommendations are summarized as follows.

First, to better promote green technology innovation, the differences between different regions should be fully considered. In regions with medium and low levels of economic development, the government shouldn't only rely on ER to force enterprises to carry out innovative R&D activities. Instead, appropriate supporting policies should be adopted to stimulate the productivity of green technological innovation. For example, the government can increase fiscal expenditures for education, thereby strengthening the training of R&D talents and enhancing regional R&D capabilities. Alternatively, the government can raise fiscal expenditures on science and technology to ensure that R&D activities in regions with medium and low levels of economic development can get corresponding financial support. In addition, the government should also reinforce inter-regional technical cooperation, improve the R&D capabilities of regions with medium and low levels of economic development through the spillover effects of technological innovation, and give full play to the leading role of regions with high economic development levels.

Second, the government should implement differentiated ER policies to ensure that the positive effects of ER on upgrading the industrial structure can enter into force. In addition to forcing the industrial structure to upgrade by means of environmental governance, the government should also guide the independent transformation of the industries by improving the economic benefits of the environmental protection industries. Besides, effective policies should be promulgated to increase social investment in the green industry projects to guide green industrial development rationally. And inter-regional cooperation in sectors should also be strengthened to promote the development of high-tech industries in regions with low economic development levels.

The limitations of this paper are as follows. When constructing the explained variable (i.e. industrial structure upgrading), this paper uses the ratio of the added value of the tertiary industry to that of the secondary industry as the proxy variable. However, changes in the added value of industries cannot reflect the differences in productivity and technical complexity of various industries. How to construct the index of industrial structure upgrading of Chinese cities from a more comprehensive perspective is worthy of attention in future work.

Declarations of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105247.

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