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ABSTRACT

It is of great theoretical and practical implications for developing countries to achieve the win-win for economic growth and environmental performance. Extant studies focus on the local effect of environmental regulation, but ignore the neighborhood effect. This study tries to fill the gap from both the theoretical analysis and empirical test. We construct the theoretical framework of the local-neighborhood effect of environmental regulation on regional green productivity growth (GPG). Based on the panel data of 237 cities in China from 2011 to 2020, we employ the spatial panel models to empirically examine the local-neighborhood effects of environmental regulation on regional GPG. We further use the mediating effect models to examine the mechanism of environmental regulation affecting neighborhood GPG. The results demonstrate that both the local and neighborhood effect on regional GPG are U-shaped. The difference is that the inflection point of neighborhood effect is larger than that of local effect. The stringency of environmental regulations implemented by most cities in China is on the left side of the inflection point of the U-shaped curve, which leads to the inhibition of local and neighborhood GPG. Moreover, both green technology spillover mechanism and pollution transfer mechanism play a significant mediating role in the neighborhood effect of environmental regulation. The competition between these two mechanisms determines the U-shaped feature of neighborhood effect of environmental regulation. Finally, we put forward policy suggestions for the GPG from the perspective of local-neighborhood effect of environmental regulation.

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1. Introduction

Emerging economies have been generally confronted with the environmental pollution in the process of rapid economic development in recent years (Sarkodie & Strezov, 2019). As the largest developing country in the world, China's GDP ranks second in the world, but its environmental pollution has become increasingly serious

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in recent years. China emitted 6.96 million tons of sulfur dioxide, 1785.22 tons of nitrogen oxides, 7.96 million tons of soot and 21.44 million tons of chemical oxygen demand in 2017[1]. The deterioration of ecological environment has become a severe challenge to the sustainable development of the economy in China. How to achieve the win-win for economy and environment has become an urgent task for the Chinese government. Furthermore, due to the negative externalities of environmental pollution, it is important not only for China to achieve green and sustainable development, but also for the whole world.

The ecological environment has the attribute of public goods. Enterprises have no motivation to improve the environment in the absence of regulation, which provides a theoretical basis for government environmental regulation. The conclusions of extant studies are inconsistent about the effects of environmental regulations on green growth. One opinion proposes that environmental regulation cannot achieve regional green productivity growth. Although environmental regulation can improve the regional ecological environment, it reduces the regional productivity because it imposes additional compliance costs on enterprises (Ederington, 2010; Lee, 2008). On the contrary, another view holds that environmental regulation can promote regional green productivity growth. Environmental regulation can stimulate enterprises in the region to develop cleaner production technologies, so that the green innovation effect exceeds the compliance cost effect, thus achieving a win-win situation of regional productivity growth and environmental performance (Alpay et al.,2002; Lanoie et al., 2008).Some recent studies have found that the impact of environmental regulations on green growth is not simply a hindrance or promotion, but a non-linear relation between them (Wang & Shao, 2019). Although some studies have explored the influence of environmental regulations on regional green growth, they only focused on the local effect and neglected the neighborhood effect.

The marginal contributions of this study are as follows. First, this article investigates the impacts of environmental regulation on regional GPG from a local-neighborhood perspective, which differentiates from previous studies that only focus on the local effect of environmental regulation. Second, this article constructs the theoretical framework of the local-neighborhood effects of environmental regulation on regional GPG, and empirically tests the impact mechanism of the neighborhood effect. On this basis, we offer a new explanation for the U-shaped relation between environmental regulation and neighborhood GPG. Third, we measure the local and neighborhood effects of environmental regulations on regional GPG based on spatial panel model. In addition, this paper uses urban data to measure the effects of environmental regulations, which is more accurate than most extant studies employing provincial data.

2. Literature review and theoretical framework

2.1. The local effect of environmental regulation

Regarding the economic effects of environmental regulations, there are two opposite theoretical hypotheses, compliance costs hypothesis and innovation compensation hypothesis. The compliance costs hypothesis holds that environmental regulations impose the costs of pollution abatement on enterprises and crowd out the productive investment, thus reducing the regional productivity (Gray & Shadbegian, 2003). The innovation compensation hypothesis is also known as Porter hypothesis. The theory posits that properly designed environmental regulation policies can stimulate innovation behaviors of enterprises, and the benefits brought by innovation offset the rising costs due to environmental regulation, so as to achieve the win-win for regional productivity growth and environmental performance (Porter & Van der Linde, 1995).

The compliance costs hypothesis and the innovation compensation hypothesis provides the theoretical basis for the local effect of environmental regulation. We hold that the impacts of environmental regulation on local GPG rely on the competition between these two theories. Enterprises usually invest in the emission abatement devices in response to environmental regulation in the short term (Hamamoto, 2006). On the other hand, as output of green technologies R&D usually takes a long time, it is difficult to demonstrate the contribution of green technologies innovation to local GPG in the short run (Zhang et al.,2011). Therefore, the influence of environmental regulation on local GPG is mainly manifested as compliance cost effect in the short run, which results in the negative relationship between local GPG and environmental regulation. In the long run, enterprises' continuous green technology R&D will achieve results. At this point, the innovative compensation effect of environmental regulation begins to appear. With the increasing stringency of environmental regulations, the innovative compensation effect gradually exceeds the compliance costs effect and occupies the dominant position, which leads to the positive relationship between local GPG and environmental regulation in the long run. Therefore, the competition between compliance costs theory and innovation compensation theory determines the U-shaped relation between local GPG and environmental regulation stringency.

2.2. The neighborhood effect of environmental regulation

When a region improves the intensity of environmental regulation, the polluters in the region have two options to respond. On the one hand, polluting enterprises can stay locally for green technologies innovation, and the flow of green innovative factors to surrounding regions will promote the green productivity of neighborhood. On the other hand, polluting companies can also relocate to regions with weak environmental regulation, resulting in the deterioration of the neighborhood environment. The neighborhood effect of environmental regulation is formed under the joint influence of these two mechanisms.

The theoretical basis of pollution transfer mechanism is pollution haven hypothesis. Polluting enterprises tend to be located in regions with weak environmental regulations according to this theory. Strict environmental regulations impose high compliance costs on polluting enterprises within the jurisdiction. In order to avoid this extra costs, polluting enterprises migrate to regions with low environmental regulation intensity, resulting in trans-regional transfer of pollution (Copeland & Taylor, 2004). The pollution haven hypothesis in China has been confirmed by a great deal of empirical research (Dou & Han, 2019). Furthermore, China's decentralization governance structure and performance assessment mechanism have led to ‘race to the bottom’ of local governments in formulating and implementing environmental regulations (Hong et al., 2019). Local governments have the incentive to attract investment by reducing the intensity of environmental regulation, thereby achieving economic growth. Such a mechanism would further strengthen the transfer of pollution between regions, causing polluting enterprises to cluster in less developed regions, thus reducing the green productivity.

The theoretical basis of green technology spillover mechanism is the new economic geography theory. The theory holds that R&D elements have significant positive externalities to economic activities. The cross regional flow of green innovation elements can lead to spatial spillover of green technology, thus promoting regional green growth (Caragliu & Nijkamp, 2016). Extant studies show that green technology achieve the spatial spillover through the following three mechanisms. Firstly, talent flow mechanism. The flow of talents among regions leads to the spatial spillover of knowledge and technologies, and accelerates the output of green technologies, thereby boosting the growth of regional green productivity (Filatotchev et al.,2011; Tambe & Hitt, 2014). Secondly, the training effect, demonstration effect and industry correlation effect brought by interregional investment and trade (Spithoven & Merlevede, 2022). (1) Companies that invest across regions often adopt localization strategies, such as training local employees and involving local technicians to participate in R&D activities. This localization process will make technologies from other regions overflow locally (Braunerhjelm et al., 2018). (2) Cross regional investment and trade brings new green production technologies to the local region, which is conducive to local enterprises to learn and imitate new technologies, so as to form the spatial spillover of green technology (Liu, 2008). (3) There is inter-industry cooperation between foreign and local enterprises, such as the cooperation formed by the upward or downward extension of the industrial chain. The exchange of enterprises in the process of cooperation is conducive to the spillover of foreign green production technology to local enterprises (Le & Pomfret, 2011). Thirdly, technical cooperation between regions. The exchange and cooperation between enterprises, research institutions and universities among regions is conducive to the spatial spillover of green technologies. For example, the talent exchange mechanism between research institutions and universities contributes to the spatial spillover of green technology among regions. On the other hand, the cooperation between enterprises and research institutions contributes to the effect of green technology in promoting green productivity (Trippl, 2013).

Green technology spillover mechanism and pollution transfer mechanism jointly determine the neighborhood effect of environmental regulation. Green technologies R&D are difficult to produce results in a short term, so the spatial spillover of green technology to adjacent areas is difficult to appear, and the pollution transfer mechanism plays the dominant role. The relative strength of the effect of these two mechanisms leads to a negative relationship between neighborhood GPG and environmental regulation stringency. With the increasing stringency of environmental regulation, the impact of green technology spillover mechanism gradually exceeds that of pollution transfer mechanism, which leads to a positive relationship between neighborhood GPG and environmental regulation in the long run (Dong et al., 2020). Therefore,

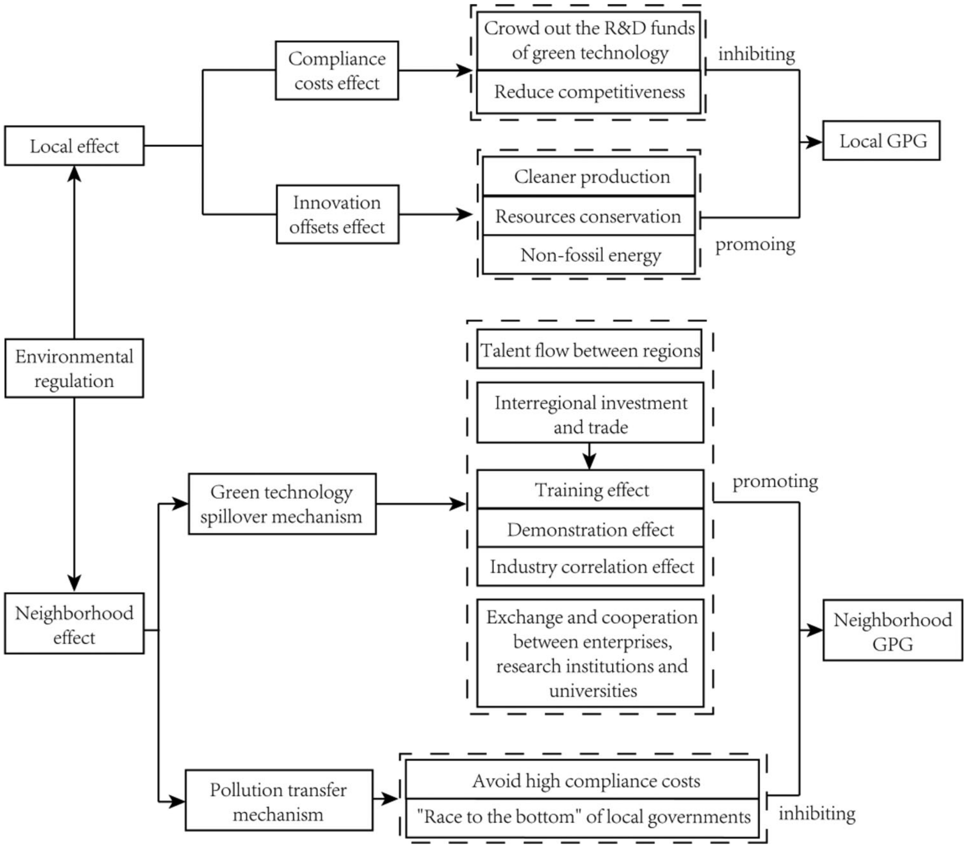

Figure 1. Theoretical framework.
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the relative strength between the effect of green technologies spillover mechanism and the effect of pollution transfer mechanism determines the U-shaped relation between neighborhood GPG and environmental regulation stringency.

Based on the above theoretical discussion, we propose the theoretical framework of local-neighborhood effect of environmental regulations on regional GPG in Figure 1.

3. Main variables and empirical facts

3.1. The measure of GPG

3.1.1. SBM model considering undesirable output

Green productivity includes environmental factors in the framework of traditional productivity, so as to comprehensively consider the relationship between resources, environment and growth. Pollutants are generally regarded as undesirable outputs. In order to deal with the undesirable outputs, Chung et al. (1997) put forward the DDF model. However, this model assumes that the expansion of expected outputs and the reduction of input factors and undesirable outputs are strictly proportional, which may result in 'slack bias' (Fukuyama & Weber, 2009). In view of this, this paper adopts slack-based measure (SBM) to deal with the undesirable outputs and construct the Malmquist productivity index.

We treat each region as a decision-making unit (DMU). Each unit has three types of input-output indicators, i types of inputs, m types of expected outputs and n types of unexpected outputs. According to Tone (2001), we construct the following non-radial and non-angle SBM model.

$$\begin{gathered} \text{s.t.} \sum_{j=1}^{J} \lambda_j x_{ji} + s_i^x = x_i, 1, \ldots, I \\ \sum_{j=1}^{J} \lambda_j y_{jgm} - s_m^g = y_m, m = 1, \ldots, M \\ \sum_{j=1}^{J} \lambda_j y_{jbn} + s_n^b = y_n, n = 1, \ldots, N \\ \lambda_j, s_i^x, s_m^g, s_n^b \geq 0 \end{gathered} \tag{1}$$

$$\rho = \min \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \frac{s_i^x}{x_i}}{1 + \frac{1}{M+N}\left(\sum_{m=1}^{M} \frac{s_m^g}{y_{gm}^g} + \sum_{n=1}^{N} \frac{s_n^b}{y_{bn}^b}\right)}$$

Where ρ represents DUM's green total factor productivity.

3.1.2. Variables

Using SBM and LM to measure green productivity index involves input and output variables, which are described below.

1. Labor input. Measure labor input by urban employment.
2. Capital investment. Capital input is measured by the estimated capital stock. Select the fixed asset investment index and use the perpetual inventory method to estimate the actual capital stock. The calculation formula is as follows:

$$K_t = (1-\delta)K_{t-1} + I_t/P_t \tag{2}$$

   where K are the actual capital stock; I is nominal investment in fixed assets; P is fixed asset price index; δ is depreciation rate of fixed assets; 2011 is the base period.
3. Energy input. It is measured by the total energy consumption converted into standard coal.
4. Desired output. Urban industrial output is selected as the expected output, and the year 2011 is taken as the base period, and the price is adjusted by PPI.
5. Undesired output. The measurement of undesired output includes 4 categories of indicators, including CO2 emissions, industrial waste water emissions, industrial waste gas emissions and industrial solid waste emissions. Since the data of CO2 emissions cannot be obtained directly, this paper uses the method provided by the United Nations Intergovernmental Panel on Climate Change (IPCC) to estimate CO2 emissions.

$$CO_2 = \sum_{i=1}^{3} E_i \times NCV_i \times CEF_i \times COF_i \times (44/12) \tag{3}$$

Where E is the consumption of coal, oil and natural gas; NCV is the average low calorific value of all kinds of energy. CEF is carbon emission coefficient; COF is the carbon oxidation factor, which is set at 0.99 for coal and 1 for crude oil and natural gas. 44 and 12 are molecular weights of carbon dioxide and carbon, respectively.

3.2. The spatial correlation of GPG

To judge whether regional GPG is suitable for the use of spatial panel model, we should first explore whether there is a significant spatial correlation in GPGs among regions. So the Moran's I index is employed to examine the spatial dependence degree of regional GPG (Anselin, 1988).

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{4}$$

Where $S^2 = (1/n)\sum_{i=1}^{n}(X_i - \bar{X})^2$; X_i is the observed value of region i; W denotes spatial weight matrix; The value range of Moran's I index is [-1,1], and its absolute value represents the degree of spatial correlation.

Before calculating Moran's I index, we must first define the spatial weight matrix, which represents the adjacent relationship among regions. The adjacent relation in spatial econometrics includes both geographical and economic adjacent relation.

(1) Spatial weight matrix based on geographical features
This type of spatial weight matrix usually includes geographically adjacent matrix and geographical distance matrix. Geographically adjacent matrix cannot reflect the spatial effect between geographically close but not adjacent regions because it only represents the spatial correlation between regions based on whether the spatial units are adjacent or not. Therefore, we choose the spatial weight matrix of geographic distance to represent the spatial effect among regions, it is defined as follows:

$$W_{ij}^{d} = \begin{cases} 1/d_{ij}, i \neq j \\ 0, \text{ otherwise} \end{cases} \tag{5}$$

Where d_{ij} is the geographical distance between two regional capitals.

(2) Spatial weight matrix based on economic features
The mutual influence between regions may also come from economic correlation.

$$W_{ij}^{e} = W_{ij}^{d} \cdot diag(\overline{Y_1}/\bar{Y}, \overline{Y_2}/\bar{Y}, \ldots, \overline{Y_N}/\bar{Y}) \tag{6}$$

where Y_i is the regional average GDP, and $\bar{Y}$ is the average GDP of all sample regions.

Table 1. Results of spatial correlation of regional GPG.

	W_1		W_2			W_1		W_2	
Year	Moran I	Z-Value	Moran I	Z-Value	Year	Moran I	Z-Value	Moran I	Z-Value
2011	0.199***	2.706	0.240***	3.372	2016	0.233***	3.176	0.268***	3.394
2012	0.206***	3.041	0.247***	3.605	2017	0.238***	3.497	0.265***	3.767
2013	0.224***	3.382	0.256***	3.517	2018	0.236***	3.169	0.272***	3.597
2014	0.226***	3.009	0.260***	3.293	2019	0.245***	3.326	0.276***	3.453
2015	0.239***	3.285	0.267***	3.578	2020	0.246***	3.283	0.274***	3.210

Note: *** denote significant levels at 1%.
Source: Author's calculation.

The results in Table 1 show that Moran's I Index among cities in China is highly significant, which indicates that the GPGs among regions have a significant positive correlation in space, and regions with similar GPG cluster together.

3.3. The measurement of environmental regulation

This paper selects four single indicators: industrial sulfur dioxide removal rate, industrial dust removal rate, comprehensive utilization rate of industrial solid waste and sewage treatment rate to construct a comprehensive index to measure the stringency of environmental regulation. First, standardize individual indicators: $SP_{ijt} = [pe_{ijt} - \min(pe_j)]/[\max(pe_j) - \min(pe_j)]$, where pe represents the original value of single pollution indicator. SP is the standardized value of single pollution indicator. Then the following method is used to determine the weight of each individual pollution indicator in each sample city, $W_{ijt} = \frac{pe_{ij}}{\sum_i pe_{ij}} / \frac{gdp_i}{\sum_i gdp_i}$. Finally, the stringency of environmental regulation is $ER_{it} = \sum_{j=1}^{4} W_{ijt}SP_{ijt}/4$. In addition, in order to ensure the robustness of results, we use other measures of environmental regulation intensity in the robustness checks.

Based on the measure of regional GPG and the stringency of environmental regulation, the relation between GPG and ER stringency is plotted. It can be seen from Figure 2 and 3 that there is a U-shaped relation between GPG and ER stringency, both locally and neighborly. Most samples are located on the left side of the inflection point for both local effect and neighborhood effect. The fitting curves between GPG and environmental regulation support the theoretical analysis conclusion in Section 2 and provide the basis for the following models construction.

4. Empirical methodology

4.1. Spatial panel model

The analysis results in Section 3.2 show that regional GPG has spatial dependence. This breaks the basic assumption of mutual independence in classical statistical analysis and econometric analysis, so that the estimation results of ordinary panel model may be biased. The spatial panel model can solve the spatial correlation, so it is necessary to construct the spatial panel model. Eq. (7) is a general nested model with three types of spatial effects, which considers the spatial correlation of explained variable, explanatory variable and error term. Eq. (7) is a spatial lag

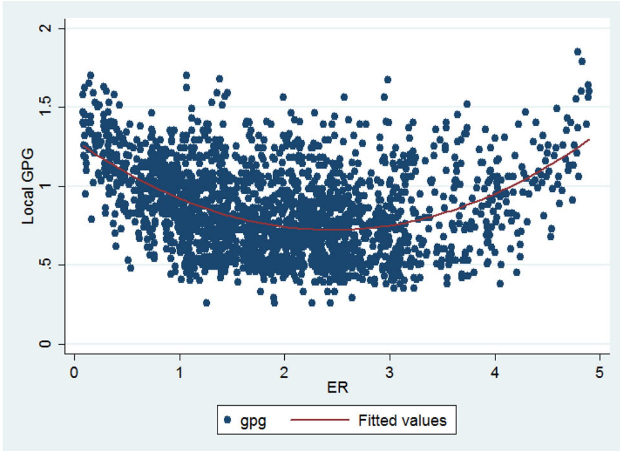

Figure 2. Fitting curve for ER and local GPG.
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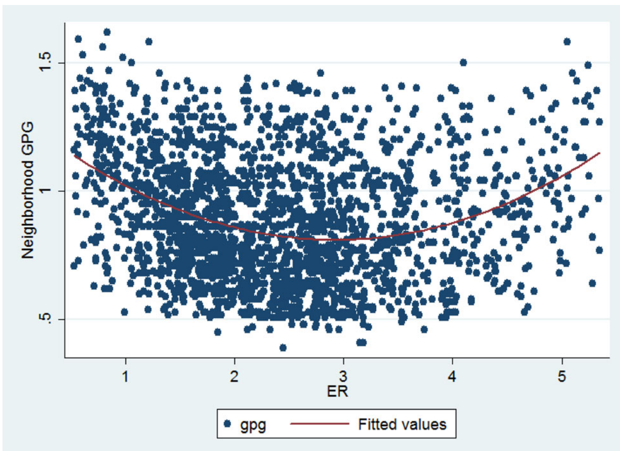

Figure 3. Fitting curve for ER and neighborhood GPG.
Source: Created by authors.

model (SLM) when $\rho \neq 0$, $\theta = 0$ and $\varphi = 0$; Eq. (7) is a spatial error model (SEM) when $\varphi \neq 0$, $\rho = 0$ and $\theta = 0$; Eq. (7) is a spatial Durbin model (SDM) when $\rho \neq 0$, $\theta \neq 0$ and $\varphi = 0$. We will determine the optimal model through a variety of test methods.

$$GPG_{it} = \tau GPG_{i,t-1} + \rho \sum_{j=1}^{n} W_{ij} GPG_{jt} + \beta_1 ER_{it} + \beta_2 ER_{it}^2 + \theta_1 \sum_{j=1}^{n} W_{ij} ER_{jt} + \theta_2 \sum_{j=1}^{n} W_{ij} ER_{jt}^2$$
$$+\gamma \sum X_{it} + \zeta \sum_{j=1}^{n} W_{ij} X_{jt} + \mu_i + \nu_t + \varepsilon_{it}, \varepsilon_{it} = \varphi \sum_{j=1}^{n} W_{ij} \varepsilon_{jt} + u_{it} \tag{7}$$

Based on the theoretical analysis in Section 2 and the fitting curves in Section 3, the relation between regional GPG and environmental regulation may be a quadratic curve, so we add the quadratic term of environmental regulation into Eq. (7). W is a spatial weight matrix. X is a set of control variables. μi, vt and εit is individual effect, temporal effect and error term respectively.

In order to investigate whether green technology spillover and pollution transfer play the mediating role in the neighborhood effects of environmental regulation on regional GPG, we construct the following mediating effect models.

$$\begin{aligned} M_{it} = \tau M_{i,t-1} + \rho\sum_{j=1}^{n} W_{ij}M_{jt} + \beta_1 ER_{it} + \beta_2 ER_{it}^2 + \theta_1\sum_{j=1}^{n} W_{ij}ER_{jt} + \theta_2\sum_{j=1}^{n} W_{ij}ER_{jt}^2 \\ +\gamma\sum X_{it} + \zeta\sum_{j=1}^{n} W_{ij}X_{jt} + \mu_i + v_t + \varepsilon_{it}, \varepsilon_{it} = \varphi\sum_{j=1}^{n} W_{ij}\varepsilon_{jt} + u_{it} \end{aligned} \tag{8}$$

$$\begin{aligned} GPG_{it} = \tau GPG_{i,t-1} + \rho\sum_{j=1}^{n} W_{ij}GPG_{jt} + \beta_1 ER_{it} + \beta_2 ER_{it}^2 + \theta_1\sum_{j=1}^{n} W_{ij}ER_{jt} \\ + \theta_2\sum_{j=1}^{n} W_{ij}ER_{jt}^2 + \eta_1 GT_{it} + \eta_2 P_{it} + \lambda_1\sum_{j=1}^{n} W_{ij}GT_{jt} + \lambda_2\sum_{j=1}^{n} W_{ij}P_{jt} \\ + \gamma\sum X_{it} + \zeta\sum_{j=1}^{n} W_{ij}X_{jt} + \mu_i + v_t + \varepsilon_{it}, \varepsilon_{it} = \varphi\sum_{j=1}^{n} W_{ij}\varepsilon_{jt} + u_{it} \end{aligned} \tag{9}$$

where M is the mediating variables, consisting of green technology (GT) and pollutants emission (P). If both the estimated coefficient θ in Eq. (8) and λ_1 in Eq. (9) are statistically significant, then green technology spillover mechanism plays the significant mediating role in the neighborhood effect. If both the estimated coefficient θ in Eq. (8) and λ_2 in Eq. (9) are statistically significant, then pollution transfer mechanism plays the significant mediating role in the neighborhood effect.

4.2. Variables

4.2.1. Explained variable and explanatory variable

The explained variable is green productivity growth (GPG) and the explanatory variable is environmental regulation stringency. We have presented their measures in Section 3.

4.2.2. Mediating variables

The mediating variables are green technology (GT) and pollutants emission (P). We collect the data of green patents from the patent database of China National Intellectual Property Administration, according to Green Patents codes in the list of patents provided by the World Intellectual Property Organization (WIPO)[2]. Then the natural logarithm of the total number of green patents in each region is taken as the measurement of green technology. We use a comprehensive index to measure pollutants emission. Specifically, we select five types of pollutants indicators, including industrial waste water discharges, chemical oxygen demand in industrial wastewater, industrial sulfur dioxide emissions, industrial soot emissions and industrial solid waste discharges, and then employ entropy weight method to calculate the comprehensive index of environmental pollution. The data for measuring pollutants emission are from China Environmental Yearbook and Provincial Statistical Yearbook.

4.2.3. Control variables

Control variables are as follows. Urbanization rate (UR). We employ the proportion of urban population to the total population in a region to measure the urbanization rate. On the one hand, the rise of urbanization leads to an increase in pollutants emissions and energy consumption, resulting in the decline of regional GPG. On the other hand, when the urbanization rate exceeds the inflection point, the R&D and application of green technology will boost the regional GPG. Therefore, we introduce both the UR and UR^2 into the model, and predict a U-shaped relationship between regional GPG and urbanization rate. Human capital (HC). We measure the level of human capital by using the proportion of people receiving higher education in the total population of a region. Industrial structure (IS). We employ the proportion of the outputs of tertiary industry in regional GDP to measure the industrial structure. Energy structure (ES). We employ the proportion of coal consumption in the total energy consumption of a region to measure the energy structure. R&D expenditure (RD). We use the ratio of R&D expenditure to regional GDP to measure R&D. R&D contribute to the use of environmentally friendly raw materials and production processes, as well as renewable energy, thereby increasing regional GPG. However, the technological bias of R&D is not necessarily green technology, but may be to increase production. Therefore, its coefficient conforms to be uncertain. Degree of openness (OPEN). We employ the proportion of FDI in regional GDP to measure the degree of openness. Opening up contributes to the introduction and application of foreign green technologies, so as to achieve green production. However, FDI may also be caused by the relatively low intensity of environmental regulation in developing countries, which leads to the 'pollution haven effect'. Therefore, its coefficient conforms to the uncertainty. Marketization degree (MAR). We measure the marketization using the share of private sector workers in a region's workforce. Marketization is conducive to improving the efficiency of resource allocation, thus promoting the regional GPG. The regression coefficient is expected to be positive.

4.3. Data

There are 293 prefecture level and above cities in mainland China by the end of 2020. 56 cities are not included in our study sample due to missing data. These cities are located in Inner Mongolia, Gansu, Xinjiang, Qinghai, Tibet, Guizhou and Yunnan provinces. In addition, Hong Kong SAR, Macao SAR and Taiwan province are not included in the sample for the inaccessibility of data. We finally have a panel data sample of 237 cities in China for the period from 2011 to 2020. The data of labor, capital, energy consumption, GDP, sulfur dioxide, nitrogen oxides, waste water, and dust involved in measuring GPG are from China Environmental Yearbook, China

Table 2. Results of the LM test, LR test and Wald test.

	W_1		W_2	
Test	Statistics	P-value	Statistics	P-value
LM-lag	509.60	0.00	527.83	0.00
LM-error	335.26	0.00	339.91	0.00
Robust LM-lag	142.64	0.06	155.07	0.02
Robust LM-error	69.43	0.21	74.28	0.14
LR spatial lag	246.37	0.00	262.65	0.00
LR spatial error	129.82	0.00	133.38	0.00
Wald spatial lag	137.57	0.00	142.95	0.00
Wald spatial error	86.72	0.00	95.46	0.00

Note: W1 and W2 is the geographic distance spatial weight matrix and the economic distance spatial weight matrix, respectively.
Source: Author's calculation.

Environment Statistics Yearbook and China Statistical Yearbook. The data for measuring environmental regulations come from China Environmental Yearbook and China Environment Statistics Yearbook. The data of control variables are from CSMAR Database and CEIC Database.

5. Results and discussions

5.1. Model selection and Estimation method

Before estimating the models, we first need to choose the most suitable one among the three competing models: SLM, SEM and SDM. The results in Table 2 show that the significance level of Robust LM-lag is higher than that of Robust LM-error, indicating that SLM is superior to SEM. Furthermore, the results of LR and Wald tests both reject the null hypothesis at 1% significance level (H0: SDM is not selected), indicating that SDM cannot be simplified to SLM or SEM. In addition, the above results are consistent for the two spatial matrices. Therefore, SDM is chosen.

To ensure the robustness of the estimated results, we report and compare the estimated results of ordinary dynamic panel model, static spatial panel model and dynamic spatial panel model respectively. The ordinary least squares, fixed effect and random effect may obtain biased results for estimation of dynamic spatial panel model (Elhorst, 2014). Therefore, in order to overcome the potential endogeneity, the system GMM (SGMM) and spatial SGMM (SSGMM) are employed to estimate the ordinary dynamic panel model and dynamic spatial panel model respectively (Arellano & Bover, 1995); The maximum likelihood estimation (MLE) is employed to estimate the static spatial panel model (Elhorst, 2003). In addition, we conduct two tests on the results of GMM. One is Sargan test, which is used to check the validity of instrumental variables; The other is AR(2) test, which is used to test whether there is second-order sequence correlation of residuals (Arellano & Bond, 1991).

5.2. The local-neighborhood effects of environmental regulation on regional GPG

Table 3 reports the local-neighborhood effects of environmental regulation on regional GPG. Firstly, the estimation coefficients of the quadratic term of

Table 3. Estimated results of environmental regulation on regional GPG.

		Ordinary dynamic panel model (SGMM)		Static spatial panel model (MLE)		Dynamic spatial panel model (SSGMM)	
		W_1 (1)	W_2 (2)	W_1 (3)	W_2 (4)	W_1 (5)	W_2 (6)
	GPG_{t-1}	0.587***	0.653***			0.394***	0.418***
		(4.20)	(3.83)			(3.95)	(3.51)
Local effect	ER	−0.960**	−0.927**	−0.613**	−0.579***	−0.492**	−0.577**
		(-2.08)	(-2.40)	(-2.52)	(-2.81)	(-2.53)	(-2.40)
	$(ER)^2$	0.239	0.234*	0.119**	0.104**	0.107***	0.121***
		(1.52)	(1.81)	(2.28)	(2.43)	(2.67)	(2.92)
	UR	−0.272*	−0.364*	−0.328*	−0.255**	−0.146**	−0.167**
		(-1.80)	(-1.69)	(-1.70)	(-1.97)	(-2.05)	(-2.24)
	UR^2	0.002**	0.003*	0.002*	0.001**	0.001*	0.001*
		(2.10)	(1.75)	(1.83)	(2.04)	(1.80)	(1.93)
	HC	0.051	0.123*	0.188**	0.104**	0.046**	0.042**
		(1.59)	(1.72)	(2.09)	(2.27)	(2.31)	(2.08)
	IS	0.069**	0.149*	0.071**	0.031***	0.022***	0.015***
		(2.19)	(1.85)	(2.33)	(2.61)	(2.94)	(2.77)
	ES	−0.014	−0.013	−0.016*	−0.018**	−0.018***	−0.019***
		(-1.50)	(-1.29)	(-1.84)	(-2.13)	(-3.10)	(-3.62)
	RD	0.350*	0.832*	0.471*	0.334	0.269	0.290
		(1.69)	(1.93)	(1.76)	(1.51)	(1.53)	(1.62)
	OPEN	0.046	0.065*	−0.038	−0.044	−0.045	−0.048
		(1.42)	(1.67)	(-1.25)	(-1.08)	(-1.36)	(-1.09)
	MAR	0.071**	0.091	0.041*	0.034*	0.032**	0.028*
		(2.10)	(1.43)	(1.72)	(1.87)	(1.97)	(1.71)
Neighborhood effect	W·GPG			1.153***	1.038**	0.896**	1.022***
				(2.75)	(2.20)	(1.99)	(2.68)
	W·ER			−1.639*	−1.492**	−1.861**	−2.063***
				(-1.93)	(-2.27)	(-2.50)	(-2.73)
	$W\cdot(ER)^2$			0.461**	0.448*	0.337**	0.364**
				(2.04)	(1.91)	(2.36)	(2.44)
	W·UR			−0.905**	−0.734*	−0.623**	−0.669**
				(-1.98)	(-1.81)	(-2.19)	(-2.16)
	$W\cdot UR^2$			0.005*	0.004*	0.003*	0.003**
				(1.74)	(1.91)	(1.86)	(2.11)
	W·HC			0.535**	0.713**	0.089**	0.068***
				(2.32)	(2.01)	(2.16)	(2.73)
	W·IS			0.346***	0.191***	0.109**	0.088***
				(2.82)	(2.66)	(2.43)	(2.90)
	W·ES			−0.049***	−0.057**	−0.052***	−0.068***
				(-2.85)	(-2.39)	(-2.80)	(-3.05)
	W·RD			1.638	1.118	1.062	0.839
				(1.52)	(1.40)	(1.33)	(1.60)
	W·OPEN			−0.125	−0.160	−0.103	−0.152
				(-1.36)	(-1.17)	(-1.50)	(-1.32)
	W·MAR			0.147	0.119*	0.159*	0.110*
				(1.60)	(1.75)	(1.71)	(1.88)
	AR(1)	0.070	0.083			0.058	0.041
	AR(2)	0.556	0.487			0.361	0.389
	Sargan test	0.692	0.772			0.958	0.986

Note: t values are in parentheses. ***, ** and * denote significant levels at 1%, 5%, and 10%, respectively. AR (1), AR (2) and Sargan test are all p-values of statistics.
Source: Author's calculation.

environmental regulation in column (1) without considering spatial correlation are not significant statistically, while the estimation coefficients of the quadratic term of environmental regulations in column (3), (4), (5) and (6) considering spatial correlation are all significant statistically. The estimation coefficients of the spatial lag terms (W·GPG and W·ER) are both statistically significant, suggesting that the ordinary dynamic panel model that does not take into account spatial correlation may result in biased estimates. Secondly, the estimation coefficient of the temporal lag term (GPGt-1) is statistically significant, indicating that the dynamic spatial panel model is superior to the static spatial panel model. Lastly, the results of Sargan test and second-order sequence correlation test show that the instrumental variables are valid and the estimation results are not affected by second-order sequence correlation. Therefore, we focus on the estimated results of dynamic spatial panel model in the following discussion.

The results of column (5) and (6) in panel 'local effect' show that the estimated coefficient of the first term and quadratic term of environmental regulation is significantly negative and positive respectively, which indicates that the local effect of environmental regulation on GPG shows a U-shaped curve. On the other hand, the results in panel 'neighborhood effect' show that the estimated coefficient of the first term and quadratic term of the spatial lag term of environmental regulation is significantly negative and positive respectively, indicating that the neighborhood effect of environmental regulation on GPG also shows a U-shaped curve. In addition, the above estimation results are consistent for the two spatial matrices.

The estimation coefficients of the spatial econometric model cannot be directly used to discuss the marginal impact of explanatory variables on the explained variable. Using the point estimation results of the spatial econometric model to analyze the spatial spillover effect may lead to biased estimates (Elhorst,2014). The impacts of environmental regulation on regional GPG have been decomposed into direct effect and indirect effect based on LeSage and Pace (2009). Table 4 reports the direct and indirect effects of SDM.

Table 4. Direct effects and indirect effects for SDM.

	W_1			W_2		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ER	−0.446**	−1.896**	−2.342***	−0.506***	−2.078**	−2.584***
	(-2.41)	(-2.42)	(2.76)	(-2.90)	(-2.16)	(-2.95)
$(ER)^2$	0.083***	0.311***	0.394**	0.099***	0.350**	0.449**
	(2.86)	(2.59)	(2.40)	(3.49)	(2.31)	(2.30)
UR	−0.176**	−0.643**	−0.819**	−0.189**	−0.769**	−0.958**
	(-2.16)	(-2.08)	(-2.11)	(-2.37)	(-1.99)	(-2.08)
UR^2	0.001*	0.003*	0.004*	0.001*	0.003*	0.004*
	(1.91)	(1.76)	(1.82)	(1.85)	(1.92)	(1.90)
HC	0.053**	0.056**	0.106**	0.061**	0.041**	0.102**
	(2.44)	(2.05)	(2.16)	(2.36)	(2.18)	(2.13)
IS	0.022***	0.076**	0.098**	0.027***	0.056***	0.083***
	(2.75)	(2.10)	(2.42)	(3.24)	(2.61)	(2.80)
ES	−0.016***	−0.034***	−0.050***	−0.018***	−0.042***	−0.060***
	(-3.71)	(-3.02)	(-2.89)	(-3.34)	(-3.51)	(-3.76)
RD	0.338	0.793	1.131	0.451	0.728	1.179
	(1.49)	(1.40)	(1.52)	(1.57)	(1.64)	(1.59)
OPEN	−0.042	−0.071	−0.113	−0.039	−0.911	−0.950
	(-1.49)	(-1.35)	(-1.46)	(-1.26)	(-1.51)	(-1.44)
MAR	0.046**	0.108*	0.154**	0.043*	0.083*	0.126*
	(2.17)	(1.86)	(2.08)	(1.90)	(1.88)	(1.81)
Inflection point for ER	2.687	3.048	–	2.556	2.969	–

Note: t values are in parentheses. ***, ** and * denote significant levels at 1%, 5%, and 10%, respectively.
Source: Author's calculation.

The first-order coefficient of the direct effect of environmental regulation is significantly negative while the quadratic coefficient is significantly positive, indicating that there is a U-shaped relationship between environmental regulation and local GPG. Under the two spatial weight matrices, the inflection points of local effect of environmental regulation are 2.687 and 2.556 for W1 and W2 respectively. From the distribution diagram of environmental regulation intensity in Figure 2, most samples fall on the left side of the inflection point, indicating that the environmental regulation implemented by most cities in China inhibits the local GPG. Similar to the local effect, the neighborhood effect of environmental regulation is also U-shape. The inflection point is 3.048 and 2.969 for W1 and W2 respectively, larger than that of the corresponding local effect. Figure 3 shows the environmental regulation stringency of most samples is located on the left side of the inflection point, so the environmental regulations implemented by most cities in China have a negative impact on GPG in neighboring areas.

5.3. Results of the impact mechanism for neighborhood effect

It has been proved that the neighborhood effect of environmental regulation exhibits a U-shaped feature. At the same time, the theoretical analysis points out that environmental regulation affects neighborhood GPG through two mechanisms: green technology (GT) spillover and pollution (P) transfer. Next we empirically test these two theoretical mechanisms. In addition, to compare the relative effects of the two mechanisms on regional GPG, we standardized the variables in the mediating effect model. Since regional GPG follows a U-shaped relation with environmental regulation, we test the effects of green technology spillover mechanism and pollution transfer mechanism on both sides of the inflection point to investigate their explanatory power on the U-shaped relationship. We use the inflection point under the spatial matrix W1 for the empirical test here, and the inflection point under the spatial matrix W2 will be used in the robustness checks.

Table 5. Estimated results of the impact mechanisms for neighborhood effect.

	ER < inflection point of neighborhood effect			ER > inflection point of neighborhood effect		
	GT (1)	P (2)	GPG (3)	GT (4)	P (5)	GPG (6)
ER	−0.353** (-2.30)	−0.491*** (-3.53)	−0.310** (-2.15)	0.891*** (3.60)	−0.623*** (-2.88)	0.466*** (3.61)
W·ER	−0.169* (-1.74)	0.357** (2.16)	−0.226** (-2.40)	0.575*** (2.96)	0.315** (2.27)	0.407*** (2.85)
GT			0.479*** (2.76)			0.808*** (3.10)
W· GT			0.294** (2.28)			0.679*** (2.63)
P			−0.621*** (-2.97)			−0.550*** (-2.72)
W· P			−0.463** (-2.28)			−0.309** (-2.21)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: t values are in parentheses. ***, ** and * denote significant levels at 1%, 5%, and 10%, respectively.
Source: Author's calculation.

Table 5 demonstrates the results of influence mechanism of neighborhood effect. It is worth pointing out that when examining the influence mechanism of neighborhood effect, the local effect is also considered. This approach can avoid the potential biased estimates that result from considering neighborhood effect alone. The results show that when the intensity of environmental regulation is less than the inflection point, environmental regulation inhibits the green technologies innovation of neighboring areas and increases the pollution of neighboring areas. In column (3), green technologies promote the GPG of neighboring regions, while pollution reduces the GPG of neighboring regions. When the intensity of environmental regulation is greater than the inflection point, the environmental regulation promotes green technologies in the neighboring areas, but increases the pollution in the neighboring areas. In column (6) green technology significantly promotes the GPG of adjacent regions, while pollution significantly reduces the GPG of adjacent regions. The above results indicate that both green technology spillover mechanism and pollution transfer mechanism play a significant mediating role in the neighborhood effect of environmental regulation.

5.4. Robustness checks

5.4.1. Potential endogeneity

In order to overcome the potential endogeneity, we employ the first-order lag term of environmental regulation as the instrumental variable and perform 2SLS to re-estimate Eq. (7) (8) and (9). The results of the second stage are presented in Table 6.

5.4.2. Change the measure of environmental regulation

The ratio of pollution control investment to regional GDP growth is used to measure the stringency of environmental regulation, and the models are re-estimated. The results of direct and indirect effects are listed in Table 7.

Table 6. Estimated results of environmental regulation on regional GPG:2SLS.

	Ordinary dynamic panel model (SGMM)		Static spatial panel model (MLE)		Dynamic spatial panel model (SSGMM)	
	W_1	W_2	W_1	W_2	W_1	W_2
GPG_{t-1}	0.595***	0.623***			0.362***	0.379***
	(3.80)	(3.51)			(3.64)	(3.27)
ER	−1.996*	−1.860**	−0.793**	−0.718**	−1.441***	−1.583***
	(-1.92)	(-2.15)	(-2.17)	(-2.35)	(-2.92)	(-2.76)
$(ER)^2$	0.511*	0.438*	0.159**	0.137**	0.263**	0.291**
	(1.69)	(1.76)	(2.41)	(2.10)	(2.40)	(2.25)
W·GPG			1.610**	1.453**	1.288***	1.497***
			(2.30)	(2.41)	(2.73)	(2.39)
W·ER			−3.804**	−3.517**	−3.539**	−3.812**
			(-2.18)	(-2.04)	(-2.16)	(-2.39)
$W{\cdot}(ER)^2$			0.674*	0.603**	0.577**	0.625***
			(1.91)	(2.12)	(2.42)	(2.68)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: t values are in parentheses. ***, ** and * denote significant levels at 1%, 5%, and 10%, respectively.
Source: Author's calculation.

Table 7. Direct effects and indirect effects for SDM.

	W_1			W_2		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ER	−0.472***	−1.325**	−1.797**	−0.681***	−1.876**	−2.557***
	(-3.06)	(-2.24)	(2.50)	(-3.49)	(-2.42)	(-2.79)
$(ER)^2$	0.098***	0.228**	0.326**	0.134***	0.331**	0.465**
	(2.91)	(2.10)	(2.31)	(3.38)	(2.18)	(2.70)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Inflection point for ER	2.408	2.906	–	2.541	2.834	–

Note: t values are in parentheses. ***, ** and * denote significant levels at 1%, 5%, and 10%, respectively.
Source: Author's calculation.

Table 8. Direct effects and indirect effects for SDM.

	Direct effect	Indirect effect	Total effect
ER	−0.416***	−1.726**	−2.142***
	(-3.15)	(-2.30)	(2.88)
$(ER)^2$	0.079***	0.286**	0.365**
	(3.32)	(2.41)	(2.64)
Control variables	Yes	Yes	Yes
Inflection point for ER	2.633	3.017	–

Note: t values are in parentheses. ***, ** and * denote significant levels at 1%, 5%, and 10%, respectively.
Source: Author's calculation.

5.4.3. Replace the spatial weight matrix

The spatial matrix of gravity model comprehensively considers the geographical distance and economic links between regions. $W_3 = (\overline{Y_i} \times \overline{Y_j})/d_{ij}^2$, where $\bar{Y}$is the real average GDP of a sample region, d_{ij} is the geographical distance between two regional capitals. We use the spatial matrix of gravity model to re-estimate the models and list the estimation results of direct and indirect effects in Table 8.

6. Conclusions and policy suggestions

Compared with traditional productivity growth, green productivity growth (GPG) considers energy consumption and pollution emissions. As GPG reflects the sustainability of economic growth, it has received more and more attention. This paper uses slack-based model to measure regional GPG, and investigates the impacts of environmental regulation on regional GPG from a local-neighborhood perspective. Then this article constructs the theoretical framework of the local-neighborhood effect of environmental regulation on regional GPG. Based on the panel data of 237 cities in China from 2011 to 2020, we employ the spatial panel models to empirically examine the local-neighborhood effects of environmental regulation on GPG. We further use the mediating effect models to examine the mediating role of both green technologies spillover mechanism and pollution transfer mechanism in the neighborhood effect of environmental regulation. Finally the empirical results are tested for robustness, and the conclusions are as follows:

First, we construct the theoretical framework of local-neighborhood effects of environmental regulation on regional GPG. Extant studies focus on the local effect of environmental regulation, but ignore the neighborhood effect. This article fills this gap. The theoretical analysis of this paper shows that, the relative strength between the effect of green technology spillover mechanism and the effect of pollution transfer mechanism determines the U-shaped relation between neighborhood GPG and environmental regulation stringency.

Second, the local effect and neighborhood effect of environmental regulation on regional GPG are U-shaped. We estimate the inflection point of the U-shaped curve. The significance of the inflection point is that we can judge whether the current environmental regulation hinders or promotes the growth of regional green productivity basing on the relationship between the intensity of environmental regulation and the inflection point. Since the intensity of environmental regulation in most regions of China is on the left side of the inflection point of the U-shaped curve, the stringency of environmental regulation should be increased to promote the growth of regional green productivity. In addition, the inflection point of neighborhood effect of environmental regulation is larger than that of local effect, which means that with the increasing intensity of environmental regulation, the promotion effect of local green productivity can be achieved first, and then the promotion effect of neighborhood green productivity.

Third, both green technology spillover mechanism and pollution transfer mechanism play a significant mediating role in the neighborhood effect of environmental regulation. Because green technology takes longer to produce, the spatial spillover effects of green technologies are weak in the short run and strong in the long run. In the short term, the pollution transfer mechanism shows the pollution effect on the neighboring regions, which reduces the green productivity growth of the neighboring regions. In the long term, however, the relocation of polluting industries will bring economic welfare to the regions they move to, thereby enhancing green technology innovation of these regions. Thus pollution transfer mechanism promotes green productivity growth in neighboring areas in the long run. Therefore, increasing the intensity of environmental regulation not only improves local green productivity growth, but also promotes neighboring green productivity growth in the long run.

According to the above research conclusions, this article puts forward the following policy suggestions and hopes to provide reference for other developing countries.

First, the intensity of environmental regulations implemented by most cities in China is on the left side of the inflection point of the U-shaped curve, which contributes to the inhibition of regional GPG. Therefore, China should strengthen the intensity of environmental regulation to make it beyond the inflection point, so as to promote regional GPG. The impact of environmental regulation on regional GPG has not only local effect, but also neighborhood effect. Moreover, the inflection point of U-shaped curve of neighborhood effect is larger than that of local effect. This means that when the stringency of environmental regulation just exceeds the inflection point of the U-shaped curve of local effect, the neighborhood effect is still on the left side of the inflection point, and the environmental regulation still inhibits GPG in adjacent regions. Therefore, China should accelerate the improvement of environmental regulation stringency, so as to give full play to the role of environmental regulation in boosting neighborhood GPG as soon as possible.

Second, due to the neighborhood effect of environmental regulation, local governments should avoid falling into the ‘race to the bottom’ of environmental regulation.

Regions should establish a collaborative mechanism of environmental regulation policies to give full play to the spatial spillover effect of green productivity, so as to strive to achieve the overall GPG.

Third, strengthen green technology spillover mechanism and curb pollution transfer mechanism. Chinese local governments should strengthen policy support for green technologies innovation of enterprises, such as providing financing support and preferential tax policies to new energy enterprises, and formulating incentive policies for the promotion and application of new energy technologies and emission abatement technologies. Regional coordination of environmental regulation policies should be strengthened to avoid the transfer of polluting enterprises from one region to another. In short, local governments should adopt the policy of 'carrot and stick' for polluting enterprises. On the one hand, environmental regulation forces polluting enterprises to achieve emission abatement targets. On the other hand, fiscal and financial policies encourage enterprises to develop and apply green production technologies to reduce emissions from the source, so as to achieve the growth of regional green productivity.

Notes

1. The data are from China's National Bureau of Statistics, https://data.stats.gov.cn/
2. https://www.wipo.int/classifications/ipc/en/green_inventory/

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