Environmental regulation, spillover effects and green technology innovation in China*

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Abstract

Based on the panel data of 177 prefecture-level cities from 2005 to 2016 in China, this study establishes spatial panel models to analyze the impact of environmental regulation on the green technology innovation which is measured by green patents application. Firstly, the local effect of environmental regulation on green technology innovation is inhibition, implying compliance cost effect of ER on green technology investment. The neighbouring spatial effect of ER on green technology is U-shaped of first inhibition and then promotion. Secondly, The local effect is mainly affected by economic development level of the city, while the neighboring effect relates to Chinese fiscal decentralization. Thirdly, the neighbouring effect of ER on green technology innovation is the U-shaped only ranging from 200km to 700km. Fourthly, ER directly inhibits local and neighbouring regions green invention patents application, while the local and neighboring spatial effects of environmental regulation on the green utility model patents were both U-shaped of first suppression and then promotion.

*All errors are my own.

1 Introduction

The Chinese economy has been maintaining steady growth and has demonstrated remarkable achievements since the reform and opening-up policy. Along these achievements are serious environmental problems such as over-exploitation of resources and serious pollution in the stage of industrialization (Cai et al., 2016). *China's Economic and ecological GDP Accounting development Report 2018* suggested that the cost of ecological damage in China was 0.63 trillion yuan, and the cost of pollution loss was 2 trillion yuan in 2018. The total ecological cost was 2.63 trillion yuan, accounting for 2.1 percent of the annual economic and ecological GDP, an increase of 28 percent compared with 2013.

Under the circumstance of attaching importance to environmental protection (ER), the central government sets environmental protection targets from top to bottom and encourages local governments to implement environmental regulations. Environmental regulation has always been effective in addressing the externalities of environmental pollution (Bi et al., 2014; Sun et al., 2019). For long term, technology innovation is the essential solution to alleviate the contradiction between environment pollution and economic growth with the end goal of achieving a win-win in the transformation of economic development mode, resources, and environmental protection (Magat, 1978). Compared with traditional innovation, green innovation is a new type of innovation activity that combines the dual benefits of technological innovation and environmental protection (Rennings and Rammer, 2011). On the one hand, green technology innovation achieves economic benefits via traditional technology innovation. On the other hand, it realizes the internalization of external environmental pollution Dai et al. (2021). However, Stringent ER may inhibit the progress of green innovation because enterprises need to spend more compliance cost which may crowd out R&D investment. On the contrary, the relation between ER and green technology innovation can be also complicated. In a free market economy, traditional non-clean technology has advantages in profit and technology R&D, while late-comer innovation of green technology shows obvious disadvantages (Acemoglu et al., 2012). Thus it is difficult for the market itself to realize the transformation of technological progress to green direction. Under the guidance of environmental regulation policy, enterprises often change their production practices by reducing resource input or improving efficiency, thus improving production compliance and reducing production costs, and even generating new marketable products. These innovations can offset the compliance costs of environmental regulation. Therefore, the exact relationship between ER and green technology innovation need to be demonstrated in order to help adjust government environment policy.

Spatial factors should also be considered in this study. Due to the special promotion mode of officials in China, local governments have the incentive to compete against one another in spurring total investment and boosting the growth of the local economy (Yu, Zhou and Zhu, 2016). This can lead to the continuous weakening of environmental regulation intensity which helps local governments attract FDI and enterprises from other regions. The transfer of capital and enterprises will cause obvious transboundary pollution between regions, which further stimulate market demand for green technology upgrade. In a sum, regional ER policy competition and the consequent transfer of enterprises or industries will all have unclear effects on green technology innovation, implying the importance of taking spatial factors into consideration. This study probed the impact of ER on the green technology innovation from the perspective of spatial correlation of the prefecture-level cities in China on the base of theoretical analysis.

The rest of this article is organized as follows. Section 2 provides a literature review of the effects of environmental regulation on technology innovations and its spatial spillover effects; section 3 illustrates the theoretical analysis and hypothesis; section 4 introduces methodology and data sources; section 5 presents empirical results and analysis; section 6 probed heterogeneity of weight matrix and patents type; section 7 presents conclusions.

2 Literature review

With the increasing attention to environmental issues, as well as the gradual enrichment and improvement of the environmental regulation system, the effects caused by environmental regulation (ER) has attracted scholars attention.

There are two strands of literature related to this study. The first strand of literature includes the relationship between environmental regulation and green technology innovation. Two main theories explain the impact of environmental regulation on innovation. One is that the technology innovation of enterprises is restricted by environmental regulation, which is called the "restriction hypothesis" (Gollop and Roberts, 1983). Under this hypothesis, the relative profit of technology innovation determines the survival of green technology (Acemoglu et al., 2012). Investment with long-term return is huge obstacles to green technology innovation, because green technology innovation is a long-term, uncertain and high-risk innovation process. The opposite view is the "Porter hypothesis" (Porter, 1991), which argues that although appropriate environmental regulation may increase "compliance cost" in the short term, it can encourage enterprises to carry out innovation in the long term, thereby improves product quality and competitiveness. If the positive "innovation compensation effect" caused by environmental regulation outstrips negative "compliance cost effect", reasonable environmental regulation can effectively stimulate the green technology innovation of regulated enterprises (Popp, Newell and Jaffe, 2010). Porter and Van der Linde (1995*b*) further explained the mechanism through which environmental protection improves competitiveness by innovation.

In empirical researches, the relationship between ER and technology innovation is dissimilar. Porter and Van der Linde (1995*a*) proves that ER will first inhibit technology innovation, and only after a certain period will it begin to promote technology innovation. The work of Ouyang, Li and Du (2020) shows that the impacts of ER on technology 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, Ren and Chen (2017) find that the effects of ER on 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.

The second strand of literature includes spatial spillover effects of environmental regulation. Faced with stringent ER, companies can choose to relocate instead of improving green technology if the cost caused by ER is greater than the cost of relocation (Li and Du, 2021). In the context of "economy-championship-competition" in China, local officials have the incentive to weaken local ER in order to attract the industry with high output but high pollution to improve economic performance, and even may appear "race-to-bottom competition" in ER (Song, Du and Tan, 2018; Zhang, Zhang and Liang, 2017). Some developed regions tend to transfer polluting industries to backward regions and then change the industrial structure of the backward regions (Shen, Jin and Fang, 2017), eventually weakened the green technology advancement effect of ER You, Zhang and Yuan (2019).

As far as spatial effects are concerned, region with high ER are prone to lead to the transfer of polluting industries to neighboring regions. In the short term, according to negative "compliance cost effect", the increase of polluting industry in neighboring areas inhibits green technological progress. However, in the long term, transferring polluting industries will render technical change turn to environment-friendly direction.

Therefore, what impact does environmental regulation have on green technology innovation? Does stronger environmental regulation raise neighbour cities green technology innovation? Based on the perspective of prefecture cities in China, this study considers the spatial factors that have been under-considered in previous studies and explores whether environmental regulation has a spillover effect in Chinas green technology innovation. The study introduces the square term of the environmental regulation index in the spatial econometric model and discusses whether environmental regulation has a turning point.

3 Theoretical hypothesis

There are two main types of measurement methods in recent researches when depict the relationship between environmental regulation and green technology innovation because of the interaction between “compliance cost effect” and “innovation compensation effect” (Fan et al., 2021). Most studies argue that environmental regulation and green innovation simply have a linear relation, with environmental regulation inhibiting green technology innovation. According to the “restriction hypothesis”, the production burden of enterprises increases and the relative profit of enterprises decreases, thereby enterprises cannot be encouraged to invest in green technology innovation when facing stringent additional ER. To be brief,The ER increases the cost of pollution control for enterprises, thus crowding out the funds for green technology innovation.

The other popular measurement type takes non-linear formula, using a threshold model (Tao and Ju, 2016) or incorporating environmental regulation quadratic terms (Li and Du, 2021) into their models to find out how environmental regulation affects technology innovation. Despite, the inhibition at the beginning, appropriate environmental regulation policy can effectively stimulate technological innovation because of the innovation compensation effect which refers to enterprises strengthening the development of environmental protection technologies under environmental regulation, improving productivity through technological innovation. Acemoglu et al. (2012) found that the combination of government environmental pollution tax and R&D subsidy policy could promote clean technology innovation and reduce pollution emissions without sacrificing economic growth. Therefore, the effect of ER on the green technology innovation could be the U-shaped effect of first inhibition and then promotion. In the short term, ER increases the additional pollution cost of enterprises, squeezes out the R&D funds of enterprises, and reduces the innovation ability of enterprises. With the gradual improvement of ER level, the relative profit of green technology increases, and enterprises carry out green innovation can not only reduce the cost of pollution through emission reduction, but also improve the competitiveness.

H1a: The ER increases the cost of pollution control for enterprises, thus directly inhibit green technology innovation.

H1b: The effect of ER on the green technology innovation could be the U-shaped effect of first inhibition and then promotion.

Spatial factors play an important role in this study. Because of the externality of environmental pollution, the government needs to implement environmental regulation policies to regulate the production behaviour of enterprises. Since the reform of the fiscal system, the economic growth model of ”competition for growth” has been formed, local governments have the incentive to lower environmental regulation standards, and factors such as capital, labor and technology would be attracted to local areas, thus promoting local economic growth. This pattern of "race-to-bottom competition" strategically lead to the transfer of polluting enterprises. Polluting enterprises in the region with high environmental regulation tend to transfer to neighboring regions with lower environmental regulation. In the short term, according to negative "compliance cost effect", the increase of polluting industry in neighboring areas inhibits green technological progress. However, in the long term, transferring polluting industries will render technical change turn to environment-friendly direction because of "innovation compensation effect".

H2: The spatial effect of ER on the green technology innovation could be the U-shaped effect of first inhibition and then promotion.

4 Methodology and Data

4.1 Econometric methodology

According to the method proposed by LeSage and Pace (2009), this study establishes a spatial Durbin panel model to depict the impact of environmental regulation on green technological innovation in China.The spatial Durbin model (SDM) is a general form of the spatial lagged model (SLM) and spatial error model (SEM). The spatial Durbin model synthesizes the effects of the spatial lag factors of dependent and independent variables on dependent variables. Therefore, spatial Durbin model can effectively capture the spillover of environmental regulation from two dimensions of time and space. As shown by the mechanism analysis, environmental regulation could present a U-shaped characteristic to local green technology progress. At the same time, it will cause some similar or even opposite changes in the progress of adjacent cities' green technologies. This paper constructs the secondary environmental regulation and technological progress curve model, contrasting "local-neighbor" green technology progress effects of environmental regulation.

$$\begin{aligned} \ln GP_{it} =& \alpha + \rho \sum_{j=1}^{N} W_{ij} \ln GP_{jt} + \beta_1 ER_{it} + \beta_2 {ER_{it}}^2 + \beta_3 \sum_{j=1}^{N} W_{ij} ER_{it} \\ &+ \beta_4 \sum_{j=1}^{N} W_{ij} {ER_{it}}^2 + \beta_5 \mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where GP represents the number of the city's green patents application, ER indicates environmental regulation; $\mathbf{X}$ is a series of control variables, W is spatial weight matrix; $\mu_i, \upsilon_t, \varepsilon_{it}$

are city fixed effects, time fixed effects and residual respectively.

4.2 Construction of spatial weight matrix

The spatial weight matrix expresses the degree of interdependence between certain geographic or economic attribute values in different spatial regions, and it is an important part of spatial econometric analysis. In this study, the spatial adjacency weight matrix W_a, the spatial inverse distance weight matrix W_d are used to measure the spatial spillover effect. At the same time, in order to comprehensively investigate the influence of economic distance, we also construct economic distance weight matrix W_e. Economic distance weight matrix represented economic distance by regional GDP difference. The smaller the economic development distance between the two cities is, the closer the economic development level is, thus giving a larger weight. The definition is:

$$W_e = W_d \times diag(\frac{\bar{Y_1}}{\bar{Y}}, \frac{\bar{Y_2}}{\bar{Y}}, \dots, \frac{\bar{Y_N}}{\bar{Y}}) \tag{2}$$

where W_d is the spatial inverse distance weight matrix, $\bar{Y_i} = \frac{1}{T}\sum_1^T Y_{it}$ is the average GDP of the city i during the specific period and $\bar{Y} = \frac{1}{N}\frac{1}{T}\sum_1^N \sum_1^T Y_{it}$ is the average GDP of all cities during the specific period.

4.3 Spatial autocorrelation test

The Moran index (Moran's I) is often used to test whether the attribute values of spatial units have spatial correlation in the whole. The values of Moran's I are $[-1, 1]$. The closer they are to 1 and 1, the stronger would be the autocorrelation. The value of Moran's I is greater than 0 for positive correlation and less than 0 for negative correlation. Specifically, the closer the value of Moran's I is to zero, the smaller will be the correlation. The Global Moran's I is used to test the spatial correlation degree of green technology innovation in this study. The formula for Moran's I is:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{3}$$

with $S_0 = \sum_{i=1}^n \sum_{j=1}^n W_{ij}$. W, x and $\bar{x}$ represent spatial weight matrix, green technology innovation level, and the average value of green technology innovation level respectively, for city i and j.

4.4 Explanation of variables

Green patents application. This paper uses the number of green patents application to represent green technology innovation. The number of green patent applications can better represent the achievements of green technology innovation in a city in that year. In China, the application for patents must be strictly examined for its significant improvement over the prior patents. Compared with the number of green patents granted, the application requirements of green patents are more stringent, thus these patents contain higher quality. The data of green patents application are from the China Patent Full-text database of The State Intellectual Property Office (SIPO) from 2005 to 2016, which contains the application number, application date, publication number, publication date, patent name, abstract, classification number and other relevant information. In 2010, the World Intellectual Property Organization (WIPO) launched an online tool for searches of patent information related to environmentally friendly technologies[1], i.e IPC GREEN INVENTORY. This list classifies green patents into seven types: transportation, waste management, energy conservation, alternative energy production, administrative regulatory or design aspects, agriculture or forestry and nuclear power generation. According to these classification standards, the green patent application and the specific category of green patent application are matched according to the patent classification number, and further added to the level of prefecture-level cities, as the core indicator of green technology innovation level.

Environmental Regulation. According to (Hilton and Levinson, 2001), performance-based environmental regulations are used to represent command-and-control environmental regulation in this study. Based on the availability of data at the city level, we choose three indicators including industrial waste water emissions, industrial sulfur dioxide emissions and PM2.5 emissions to construct a performance-based environmental regulation index system in this study. The specific calculation steps are as follows: Firstly, The three indicators are divided by GDP to calculate unit economic pollution emissions and then standardized by min-max method:

$$SE_{it}^{j} = \frac{E_{it}^{j} - \min(E_{t}^{j})}{\max(E_{t}^{j}) - \min(E_{t}^{j})} \tag{4}$$

where E_{it}^{j} represents the unit economic pollution emissions of j type contaminant of the i city; $\max(E_{t}^{j})$ and $\min(E_{t}^{j})$ represent the maximum and minimum values of indicator j in all cities in China, respectively. SE_{it}^{j} indicates the standardized value of the contaminant j of the i city.

Secondly, set the adjustment parameters. The proportion and intensity of pollution

[1] https://www.wipo.int/classifications/ipc/green-inventory/home

emissions in different cities vary greatly, and the adjustment parameters can reflect the difference of pollution in different cities. The adjustment parameters are calculate as:

$$W_{it}^{j} = \frac{E_{it}^{j}}{\bar{E_t^j}} \tag{5}$$

Where $\bar{E_t^j}$ is the average unit economic pollution emissions of j type contaminant among sample cities. The calculation results show that if the emission of the j contaminant in the j region is relatively high, then the same pollution treatment rate would imply stronger environmental regulation, and thus the weight given would be greater (Wu, Hao and Ren, 2020).

Finally, based on the standardized values and adjustment parameters of the three individual indicators, the degree of environmental regulation of the corresponding cities is obtained:

$$ER_{it} = \frac{1}{3}\sum_{1}^{j} W_{it}^{j} SE_{it}^{j} \tag{6}$$

Control variables and data sources. This study also introduces other explanatory variables as control variables. Specifically, following the literature, we choose GDP per capita ($\ln pergdp$) to represent cities' economic development level and the R&D expenditure per capita($\ln rdintensity$) to represent technology level respectively. Additionally, the ratio of the total fiscal income of the city to that of the central government ($fiscal$) is used as the proxy variable of fiscal decentralization measurement China (Wang, 2013). As an institutional arrangement to adjust the structure of central and local resources allocation, fiscal decentralization has the potential to influence government expenditure preference and regional green innovation output. The ratio of foreign direct investment to GDP (fdi) is used to measure the effect of local government's excessive attraction of foreign capital (Hoffmann et al., 2005). According to the *pollution haven hypothesis*, weak environmental regulation in a host country may attract inward FDI by profit-driven companies eager to circumvent costly regulatory compliance in their home countries (Jensen, 1996). In the other hand, according to the *pollution halo hypothesis*, when facing stringent environmental regulation, multi-nationals will tend to spread its greener technology to their subsidiaries in the host country (Zarsky, 1999).

As a summary, the descriptive statistics of the variables involved in this study are reported in Table 2. The data for environmental regulation are obtained from the Ministry of Ecology and Environment of the People's Republic of China. The data of control variables come from China City Statistical Yearbook and National Bureau of Statistics. After dropping missing data, we construct a panel of 177 cities between 2005 and 2016.

Table 1: The statistical description of variables

Symbol	Description	Count	Mean	Sd	Min	Max
$\ln gp\_all$	Total green patents application	2124	4.353	1.838	0.000	10.123
$\ln gup$	Green utility model patents application	2124	3.775	1.756	0.000	9.010
$\ln gip$	Green invention patents application	2124	3.532	1.884	0.000	9.724
ER	Environmental regulation	2124	0.543	1.660	0.000	36.807
$\ln pergdp$	GDP per capita	2124	10.063	0.704	4.393	12.785
$\ln rd\_inten$	R&D expenditure per capita	2124	12.412	0.360	11.306	13.281
$fiscal$	Fiscal decentralization	2124	0.385	0.807	0.014	8.852
fdi	FDI*100/GDP	2124	0.331	0.296	0.000	1.876

5 Empirical Results

5.1 Spatial autocorrelation test

First, we test for cross-sectional dependence using Pesaran (2015) CD-test based on the green technology innovation of the 177 cities in China over 2005-2016 (N = 177, T = 12). The dependence between units violates the basic OLS assumption of an independent and identically distributed error term. In the worst case cross sectional dependence in the error term can lead to endogeneity and therefore to inconsistent estimates. The null hypothesis of the test is that the error term is weakly cross sectional dependent. If the null is rejected, spatial factors should be accounted for Ciccarelli and Elhorst (2018). The result is 157.699 with a high significance at 1%, indicating that spatial econometric model needs to be accounted for.

Second, the spatial correlation of green patents application ($\ln gp_a ll$) and environmental regulation ($\ln ER$) are respectively tested under the three types of weight matrices, and the results are shown in table 2.

Table 2: Global Correlation Test Moran's I

	Green patents application			Environmental regulation		
	W_a	W_d	W_e	W_a	W_d	W_e
2005	0.226***	0.051***	0.139***	0.031	0.006**	0.013
2006	0.213***	0.049***	0.134***	0.029	0.005***	0.013
2007	0.253***	0.056***	0.157***	0.022*	-0.000**	0.007***
2008	0.231***	0.062***	0.168***	0.024	0.003***	0.010
2009	0.249***	0.069***	0.176***	0.031	0.003***	0.012
2010	0.272***	0.077***	0.202***	0.034	0.009***	0.017
2011	0.318***	0.083***	0.224***	0.151***	0.023***	0.067***
2012	0.310***	0.089***	0.236***	0.245***	0.044***	0.101***
2013	0.319***	0.085***	0.229***	0.138**	0.028***	0.075***
2014	0.312***	0.090***	0.231***	0.048	0.006	0.033
2015	0.341***	0.098***	0.252***	0.007	-0.003	0.010
2016	0.355***	0.099***	0.262***	0.040	0.012	0.036

Note: *, ** and *** are significance at the 10%, 5%, and 1% confidence levels, respectively.

Table 2 suggests that, the Moran's I values of green patents application are all positive from 2005 to 2016 under all three weight matrices, that is the green technology innovation among cities has remarkably agglomerated characteristic in spatial distribution in China. In addition, the Moran's I values of environmental regulation also shows significant spatial correlation in some years. Thus, spatial econometric model is better and essential in this study.

5.2 Model Specification Test

Panel spatial econometric models mainly include the SLM, the SEM and the SDM, among which the SLM and the SEM are generally selected based on the Lagrange Multiplier (LM-lag and LM-error) of model residual and its robustness (Robust-LM-lag and Robust-LM-error) (Elhorst, 2014). Whenever using a classic LM test or robust LM test, both the null hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially error term must be rejected at 1% significance. Then the SDM needs to be considered (LeSage and Pace, 2010) and it can be tested using either a Likelihood Ratio (LR) test or a Wald test. The results of LR-lag and Wald-lag test are both highly significant at 1%, which rejects that the SDM can be simplified to the SLM. In addition, The results of LR-error and Wald-error test are both highly significant at 1%, which rejects that the SDM can be simplified to the SEM. In a sum, the SDM was further adopted for empirical analysis in this paper.

Table 3: Model specification test

Method	Statistic	P-value	Method	Statistic	P-value
LM-lag	618.2576	0.000	Wald-lag	73.4569	0.000
Robust-LM-lag	125.3056	0.000	LR-lag	82.1165	0.000
LM-error	541.2341	0.000	Wald-error	87.1811	0.000
Robust-LM-error	48.2821	0.000	LR-error	95.9649	0.000

Note: These results are all under spatial inverse distance weight matrix and are robust under other weight matrices.

5.3 Main Empirical Results

Due to the spatial spillover effect of environmental regulation, the change of environmental regulation will not only lead to the change of the local green technology innovation level, but also the change of the green technology innovation level in the neighboring area. In this subsection, the 0-1 adjacency distance weight matrix W_a, geographical inverse distance weight matrix W_d, economic distance weight matrix W_e are used to test the local effect and adjacent effect of environmental regulation on green technology progress successively. All regression models of different weight matrices adopt the city and time fixed effects.

First, from the main results of Table 4, we can find that ER has a significantly negative effect on local green patents application. This implies that the hypothesis H1a is true. The intuition behind this is simple. The ER increases the cost of pollution control for enterprises which is called "compliance cost effect", thus directly inhibit green technology innovation. In addition, the ER can not significantly improve the green technology innovation level in long term because the traditional non-clean technology is still dominant in the market, and the benefit of new green technology is limited. Under the condition of maximizing their own benefits, enterprises have no motivation to carry out green technology research and development.

Second, from the spatial estimation results of Table 4, it can be seen that regional green technology innovation has positive spillover effects, implying the importance of R&D cooperation between regions. Among all models, the coefficients of spatial lagged ER and its quadratic term are significantly negative and positive respectively. Thus, the effect of ER of neighbouring areas on local green technology innovation is the U-shaped effect of first inhibition and then promotion. The intuition behind is that when the neighboring areas improve ER level, the local ER appears relatively low, the pollution industry moves in local region and will have a dynamic impact on green technology level. In short term, on the one hand, enterprises in local region cannot afford to compliance cost of ER and squeeze out their R&D expenditure due to "compliance cost effect". On the other hand, local region often becomes the place to undertake polluting industries, which makes the industrial structure change towards non-clean direction, and inhibits the progress of green technology in local market. In long term, as the ER level of neighbouring areas increases, the government and consumers in market would prefer clean technology products which means the relative profit of green technology will increase and enterprises will have the incentive to enhance it due to "innovation compensation effect".

Table 4: The regression results of the spatial Durbin model

Variables	W_a	W_d	W_e
ER	-0.0507**	-0.0447**	-0.0397*
	(-2.3844)	(-2.1193)	(-1.9152)
ER^2	0.0007	0.0005	0.0004
	(1.1472)	(0.7449)	(0.7027)
$\ln pergdp$	0.2176***	0.1642***	0.2132***
	(3.8844)	(2.9590)	(3.8169)
$fiscal$	0.0751	0.1032	0.0840
	(1.1374)	(1.5983)	(1.3188)
fdi	-0.1327**	-0.0704	-0.0643
	(-2.2962)	(-1.2521)	(-1.1416)
$\ln rd\_inten$	0.1419	0.1412	0.0927
	(1.2901)	(1.2013)	(0.6933)
$W \times ER$	-0.1138***	-0.9197***	-0.2946***
	(-3.1271)	(-4.2467)	(-3.3155)
$W \times ER^2$	0.0023**	0.0162**	0.0048*
	(1.9759)	(2.4091)	(1.7469)
$W \times \ln pergdp$	-0.0217	0.4276	-0.0719
	(-0.2293)	(0.8559)	(-0.4933)
$W \times fiscal$	0.2009**	2.6363***	0.3904***
	(2.1504)	(3.3820)	(2.8192)
$W \times fdi$	0.0970	0.7182	0.0918
	(1.1532)	(1.5906)	(0.6657)
$W \times \ln rd\_inten$	-0.5501***	-2.6570***	-0.6746***
	(-4.4118)	(-4.8666)	(-2.8315)
$Spatial \quad rho$	0.3434***	0.9238***	0.6631***
	(14.6007)	(61.6291)	(21.5479)
City FE	YES	YES	YES
Time FE	YES	YES	YES
R^2	0.9654	0.9642	0.9646
Log-likelihood	-779.4624	-794.9547	-838.9099
N	2124	2124	2124

Note: t-values of coefficients in parentheses

According to (LeSage and Pace, 2009), we need to estimate three different effects to support the analysis because a change in the explanatory variable for a single region can potentially affect the dependent variable in all other regions. This effect includes the effect of feedback loops where region i affects region j and region j also affects observation i. The point estimation does not consider the feedback loops. Further regression results of direct, indirect and total effects of ER on green innovation were showing in Table 5.

The first panel of direct effect shows that the ER level significantly inhibits regional green patents application under two spatial weight matrices. The second panel of indirect effect shows that the ER level has a U-shaped spillover effect. The ER of neighbouring areas first inhibits and then promotes local green patents application under all spatial weight matrices.

In control variables, regional economic development level has a positive effect on green technology innovation; Fiscal decentralization also has a positive direct and spillover effect on green technology innovation in China because government financial support is helpful to the development of enterprises; Provincial technology development level has an insignificantly positive direct effect and a significantly negative indirect effect on green technology innovation, indicating that the R&D investment is mainly concentrated on traditional technologies, which may have not turned to the direction of cleaning in nowadays China.

Table 5: Three different effects of regression estimation results

	Variables	W_a	W_d	W_e
Direct Effect	ER	-0.0645***	-0.1095***	-0.0641***
		(-2.8411)	(-3.7300)	(-2.8075)
	ER^2	0.0010	0.0016*	0.0008
		(1.4364)	(1.8655)	(1.1929)
	$\ln pergdp$	0.2254***	0.2052***	0.2194***
		(4.1658)	(3.5625)	(3.8908)
	$fiscal$	0.1046	0.2867***	0.1181*
		(1.4736)	(3.1407)	(1.8527)
	fdi	-0.1279**	-0.0245	-0.0650
		(-2.2244)	(-0.4278)	(-1.1308)
	$\ln rd\_inten$	0.0897	-0.0323	0.0443
		(0.8562)	(-0.2997)	(0.3468)
Indirect Effect	ER	-0.1816***	-12.9757***	-0.9285***
		(-3.4217)	(-3.3715)	(-3.4885)
	ER^2	0.0035**	0.2256**	0.0147*
		(2.0853)	(2.2578)	(1.8013)
	$\ln pergdp$	0.0793	7.5044	0.2079
		(0.6456)	(1.1249)	(0.5321)
	$fiscal$	0.3215**	37.1930***	1.2938***
		(2.3812)	(2.8089)	(3.1109)
	fdi	0.0688	8.6785	0.1524
		(0.6173)	(1.3334)	(0.4136)
	$\ln rd\_inten$	-0.7108***	-33.9183***	-1.7907***
		(-5.0651)	(-3.5718)	(-3.4631)
Total Effect	ER	-0.2462***	-13.0852***	-0.9927***
		(-3.7590)	(-3.3814)	(-3.5980)
	ER^2	0.0044**	0.2272**	0.0155*
		(2.1704)	(2.2602)	(1.8298)
	$\ln pergdp$	0.3047**	7.7096	0.4273
		(2.2519)	(1.1520)	(1.0748)
	$fiscal$	0.4261**	37.4797***	1.4119***
		(2.5348)	(2.8162)	(3.1701)
	fdi	-0.0591	8.6540	0.0874
		(-0.4813)	(1.3261)	(0.2331)
	$\ln rd\_inten$	-0.6211***	-33.9506***	-1.7465***
		(-4.6643)	(-3.5780)	(-3.7744)

Notes: This table shows different spatial effects of environmental regulation on total green patents application

6 Heterogeneous Analysis

6.1 Examine the heterogeneity of distance cutoff

Considering the effect of environmental regulation on the progress of green technology in neighboring areas, some conditions may need to be satisfied. The effect of green technology progress in the neighboring area may have a greater impact on the area closer to the two regions. To confirm this assumption, we design method of weighting matrix with cutoff on 200 km, 250km, 300 km, 400 km, 500 km etc. to examine the model. The local spatial weight matrix was reset to investigate the effect of environmental regulation on the progress of local and neighboring green technology in urban economic circles at different distances. The results are summarized in Table 6. Estimation results of environmental regulation under different distance weight matrix are consistent with main results. For direct effect, environmental regulation significantly inhibits local green technology. For indirect effect, the effect of ER of neighbouring areas on local green technology innovation is the U-shaped effect of first inhibition and then promotion ranging from 200km to 700km. The influence of environmental regulation on the green technology progress in neighboring areas shows obvious characteristics of nearby transfer, which shows a trend of rising first and then declining. It means that the U-shaped feature of spatial effect is more valid in a specific local area, and there may be obvious errors if only the test is carried out under global distance weight matrix.

Table 6: Estimation results of heterogeneity analysis

	Variables	W_{200}	W_{300}	W_{400}	W_{500}	W_{600}	W_{700}	W_{800}
Direct Effect	ER	-0.0636***	-0.0584***	-0.0583***	-0.0564***	-0.0562***	-0.0569**	-0.0532**
		(-2.9165)	(-2.6391)	(-2.6435)	(-2.6675)	(-2.6074)	(-2.5543)	(-2.4051)
	ER^2	0.0010	0.0008	0.0008	0.0008	0.0007	0.0007	0.0006
		(1.5005)	(1.2324)	(1.1960)	(1.1861)	(1.1515)	(1.1311)	(0.9700)
Indirect Effect	ER	-0.1929***	-0.2793***	-0.3072***	-0.3527***	-0.3927***	-0.4041***	-0.3873***
		(-4.0350)	(-4.4180)	(-3.8613)	(-3.8233)	(-3.7867)	(-3.7003)	(-3.1747)
	ER^2	0.0038**	0.0047**	0.0053**	0.0064**	0.0069**	0.0069**	0.0060
		(2.5204)	(2.3919)	(2.1775)	(2.2391)	(2.1567)	(2.0557)	(1.5477)
Total Effect	ER	-0.2564***	-0.3377***	-0.3655***	-0.4092***	-0.4489***	-0.4610***	-0.4406***
		(-4.3582)	(-4.5676)	(-4.066)	(-4.0186)	(-3.9864)	(-3.8758)	(-3.3510)
	ER^2	0.0048**	0.0056**	0.0061**	0.0071**	0.0077**	0.0077**	0.0066
		(2.5700)	(2.3966)	(2.2075)	(2.2600)	(2.1930)	(2.0930)	(1.5881)

6.2 Examine the heterogeneity of green patents

Green invention patents can promote the actual green innovation of enterprises and better achieve environmental regulation goals than green utility model patents. However, utility model patents have the advantages of short innovation cycle and great practical value (Du et al., 2021). Considering the different features of the two kinds of green patents, this subsection further examines the green invention patents effects and green utility model patents effects of the environmental regulation to analyze the patent type heterogeneity. The results are summarized in Table 7. We can find that environmental regulation directly inhibits local and neighbouring region's green invention patents application because this type needs more time and investment in technology which could be seriously influenced by environmental regulation. On the contrary, the effect of environmental regulation on green utility model patents is inconsistent with main results. Environmental regulation has both U-shaped effect on local and neighbouring region's green utility model patents. Utility model patents have the advantages of short innovation cycle and great practical value so that enterprises has the incentive to apply this type to cope with environmental responsibility with the intensification of environmental regulation.

Table 7: Three different effects on different kinds of green patents

		Green invention patents			Green utility model patents		
	Variables	W_a	W_d	W_e	W_a	W_d	W_e
Direct Effect	ER	-0.0451*	-0.0627**	-0.0423	-0.0715***	-0.0989***	-0.0677***
		(-1.6956)	(-2.1121)	(-1.4967)	(-3.1341)	(-4.6082)	(-2.8207)
	ER^2	0.0006	0.0005	0.0004	0.0013*	0.0019**	0.0011*
		(0.6970)	(0.5578)	(0.4872)	(1.8720)	(2.2861)	(1.6021)
	$\ln pergdp$	0.0949	0.0946	0.1235*	0.1990***	0.1788***	0.1951***
		(1.3645)	(1.4071)	(1.7078)	(3.6120)	(2.9331)	(3.4690)
	$fiscal$	0.1631*	0.3481***	0.1814**	0.1826***	0.3312***	0.2020***
		(1.9257)	(3.4363)	(2.1698)	(2.6546)	(3.7792)	(2.8555)
	fdi	-0.2113***	-0.0992	-0.1258*	-0.0689	-0.0119	-0.0232
		(-2.9546)	(-1.4510)	(-1.8362)	(-1.1669)	(-0.2004)	(-0.4047)
	$\ln rd\_inten$	0.1676	0.1298	0.2654*	-0.0774	-0.0814	-0.0429
		(1.3233)	(0.9366)	(1.6856)	(-0.7108)	(-0.7638)	(-0.3236)
Indirect Effect	ER	-0.1616***	-7.5200**	-0.6930***	-0.1344***	-8.9448***	-0.6460**
		(-2.6439)	(-2.5457)	(-2.7633)	(-2.6613)	(-2.6555)	(-2.5038)
	ER^2	0.0025	0.0857	0.0089	0.0027*	0.2062**	0.0138*
		(1.3035)	(1.1067)	(1.1364)	(1.6786)	(2.1720)	(1.6623)
	$\ln pergdp$	0.3337**	5.6071	0.4043	-0.0052	6.8870	-0.0091
		(2.2770)	(1.0474)	(1.0698)	(-0.0429)	(1.1055)	(-0.0245)
	$fiscal$	0.4987***	38.6159***	1.7703***	0.2892**	28.0842**	1.0278
		(3.2453)	(3.1683)	(4.4350)	(2.3702)	(2.4554)	(2.5609)
	fdi	0.0882	9.8534*	0.3790	0.0292	3.2535	0.0508
		(0.7013)	(1.9310)	(1.0301)	(0.2725)	(0.5677)	(0.1362)
	$\ln rd\_inten$	-0.9396***	-29.2853***	-2.5691***	-0.5217***	-26.8264***	-1.5386***
		(-5.6740)	(-3.4478)	(-5.0636)	(-3.7225)	(-3.1856)	(-3.1234)
Total Effect	ER	-0.2067***	-7.5827**	-0.7353***	-0.2060***	-9.0437***	-0.7137***
		(-2.7752)	(-2.5557)	(-2.8221)	(-3.3563)	(-2.6705)	(-2.6660)
	ER^2	0.0031	0.0862	0.0093	0.0039**	0.2081**	0.0149*
		(1.3134)	(1.1072)	(1.1401)	(2.0532)	(2.1794)	(1.7321)
	$\ln pergdp$	0.4286***	5.7017	0.5278	0.1938	7.0659	0.1859
		(2.6922)	(1.0636)	(1.3734)	(1.4967)	(1.1299)	(0.4871)
	$fiscal$	0.6619***	38.9640***	1.9517***	0.4718***	28.4155**	1.2298***
		(3.5261)	(3.1816)	(4.5321)	(3.1817)	(2.4721)	(2.8328)
	fdi	-0.1230	9.7542*	0.2532	-0.0397	3.2416	0.0275
		(-0.9096)	(1.9096)	(0.6784)	(-0.3447)	(0.5641)	(0.0728)
	rdinten	-0.7720***	-29.1555***	-2.3037***	-0.5991***	-26.9078***	-1.5815***
		(-5.2062)	(-3.4387)	(-5.2238)	(-4.6082)	(-3.1977)	(-3.6640)

7 Conclusion

Green technology innovation is the key to solve the dilemma of environmental protection and economic growth, and environmental regulation is the main way for emerging economies to take the initiative to deal with environmental problems. This study utilized the panel data of 177 prefecture-level cities from 2005 to 2016 in China to measure the green technology innovation by green patents application, and then established spatial panel models to analyze the impact of ER on the green technology innovation.

This study found that the local effect of environmental regulation on green technology innovation was inhibition, implying that ER increases the cost of pollution control for enterprises which is called compliance cost effect, thus directly inhibits green technology investment. The neighbouring spatial effect of ER on green technology was U-shaped of first suppression and then promotion. The local effect was consistent with Porters hypothesis, mainly affected by economic development level of the city, while the neighboring effect might relate closely to Chinese fiscal decentralization.

Heterogeneous analysis examined the spatial panel model with heterogeneous distance cutoff weight matrix and analyzed the patent type heterogeneity. The former analysis found that the local effect is consistent with main results, while the neighbouring effect is the U-shaped only ranging from 200km to 700km. The latter analysis showed that environmental regulation directly inhibits local and neighbouring regions green invention patents application because this type needs more time and investment. The local and neighboring spatial effects of environmental regulation on the green utility model patents were both U-shaped of first suppression and then promotion.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous. 2012. "The Environment and Directed Technical Change." *American economic review*, 102(1): 131–66.

Bi, Gong-Bing, Wen Song, Peng Zhou, and Liang Liang. 2014. "Does Environmental Regulation Affect Energy Efficiency in China's Thermal Power Generation? Empirical Evidence from a Slacks-Based DEA Model." *Energy Policy*, 66: 537–546.

Cai, Xiqian, Yi Lu, Mingqin Wu, and Linhui Yu. 2016. "Does Environmental Regulation Drive Away Inbound Foreign Direct Investment? Evidence from a Quasi-Natural Experiment in China." *Journal of Development Economics*, 123: 73–85.

Ciccarelli, Carlo, and J. Paul Elhorst. 2018. "A Dynamic Spatial Econometric Diffusion Model with Common Factors: The Rise and Spread of Cigarette Consumption in Italy." *Regional Science and Urban Economics*, 72: 131–142.

Dai, Lihua, Xiuru Mu, Chien-Chiang Lee, and Wei Liu. 2021. "The Impact of Outward Foreign Direct Investment on Green Innovation: The Threshold Effect of Environmental Regulation." *Environmental Science and Pollution Research*, 28(26): 34868–34884.

Du, Gang, Meng Yu, Chuanwang Sun, and Zhao Han. 2021. "Green Innovation Effect of Emission Trading Policy on Pilot Areas and Neighboring Areas: An Analysis Based on the Spatial Econometric Model." *Energy Policy*, 156: 112431.

Elhorst, J. Paul. 2014. *Spatial Econometrics from Cross-Sectional Data to Spatial Panels.* Springer.

Fan, Fei, Huan Lian, Xiaoyang Liu, and Xueli Wang. 2021. "Can Environmental Regulation Promote Urban Green Innovation Efficiency? An Empirical Study Based on Chinese Cities." *Journal of Cleaner Production*, 287: 125060.

Gollop, Frank M., and Mark J. Roberts. 1983. "Environmental Regulations and Productivity Growth: The Case of Fossil-Fueled Electric Power Generation." *Journal of political Economy*, 91(4): 654–674.

Hilton, Francis, and Arik Levinson. 2001. "Measuring Environmental Compliance Cost and Economic Consequences: A Perspective from the US." *Quantifying the Impact of Technical Barriers to Trade: Can It Be Done*, 219–241.

Hoffmann, Robert, Chew-Ging Lee, Bala Ramasamy, and Matthew Yeung. 2005. "FDI and Pollution: A Granger Causality Test Using Panel Data." *Journal of International Development*, 17(3): 311–317.

Jensen, V. 1996. "The Pollution Haven Hypothesis and the Industrial Flight Hypothesis: Some Perspectives on Theory and Empirics." *Centre for Development and the Environment (Working Paper 1996.5), University of Oslo, Oslo.*

LeSage, James, and Robert Kelley Pace. 2009. *Introduction to Spatial Econometrics.* Chapman and Hall/CRC.

LeSage, James P., and R. Kelley Pace. 2010. "Spatial Econometric Models." In *Handbook of Applied Spatial Analysis*. 355–376. Springer.

Li, Jing, and YuanXin Du. 2021. "Spatial Effect of Environmental Regulation on Green Innovation Efficiency: Evidence from Prefectural-Level Cities in China." *Journal of Cleaner Production*, 286: 125032.

Magat, Wesley A. 1978. "Pollution Control and Technological Advance: A Dynamic Model of the Firm." *Journal of Environmental Economics and management*, 5(1): 1–25.

Ouyang, Xiaoling, Qiong Li, and Kerui Du. 2020. "How Does Environmental Regulation Promote Technological Innovations in the Industrial Sector? Evidence from Chinese Provincial Panel Data." *Energy Policy*, 139: 111310.

Pesaran, M. Hashem. 2015. "Testing Weak Cross-Sectional Dependence in Large Panels." *Econometric reviews*, 34(6-10): 1089–1117.

Popp, David, Richard G. Newell, and Adam B. Jaffe. 2010. "Energy, the Environment, and Technological Change." *Handbook of the Economics of Innovation*, 2: 873–937.

Porter, Michael, and Claas Van der Linde. 1995*a*. "Green and Competitive: Ending the Stalemate." *The Dynamics of the eco-efficient economy: environmental regulation and competitive advantage*, 33.

Porter, Michael E. 1991. "America's Green Strategy." *Scientific American*, 264(4): 168–168.

Porter, Michael E., and Claas Van der Linde. 1995*b*. "Toward a New Conception of the Environment-Competitiveness Relationship." *Journal of economic perspectives*, 9(4): 97–118.

Rennings, Klaus, and Christian Rammer. 2011. "The Impact of Regulation-Driven Environmental Innovation on Innovation Success and Firm Performance." *Industry and Innovation*, 18(03): 255–283.

Shen, K. R., G. Jin, and X. Fang. 2017. "Does Environmental Regulation Cause Pollution to Transfer Nearby." *Econ. Res. J*, 52: 44–59.

Song, Malin, Juntao Du, and Kim Hua Tan. 2018. "Impact of Fiscal Decentralization on Green Total Factor Productivity." *International Journal of Production Economics*, 205: 359–367.

Sun, Chuanwang, Dan Ding, Xingming Fang, Huiming Zhang, and Jianglong Li. 2019. "How Do Fossil Energy Prices Affect the Stock Prices of New Energy Companies? Evidence from Divisia Energy Price Index in China's Market." *Energy*, 169: 637–645.

Tao, Chang-qi, and Ze-xia Ju. 2016. "Threshold Effect of Environmental Regulation on Technological Innovation from the Financial Development Perspective——Two-stage Analysis Based on Value Chain Theory." *R D Manag.*, 28(1): 95–102.

Wang, Yong. 2013. "Fiscal Decentralization, Endogenous Policies, and Foreign Direct Investment: Theory and Evidence from China and India." *Journal of Development Economics*, 103: 107–123.

Wu, Haitao, Yu Hao, and Siyu Ren. 2020. "How Do Environmental Regulation and Environmental Decentralization Affect Green Total Factor Energy Efficiency: Evidence from China." *Energy Economics*, 91: 104880.

You, Daming, Yang Zhang, and Baolong Yuan. 2019. "Environmental Regulation and Firm Eco-Innovation: Evidence of Moderating Effects of Fiscal Decentralization and Political Competition from Listed Chinese Industrial Companies." *Journal of cleaner production*, 207: 1072–1083.

Yuan, Baolong, Shenggang Ren, and Xiaohong Chen. 2017. "Can Environmental Regulation Promote the Coordinated Development of Economy and Environment in China's Manufacturing Industry?–A Panel Data Analysis of 28 Sub-Sectors." *Journal of Cleaner Production*, 149: 11–24.

Yu, Jihai, Li-An Zhou, and Guozhong Zhu. 2016. "Strategic Interaction in Political Competition: Evidence from Spatial Effects across Chinese Cities." *Regional Science and Urban Economics*, 57: 23–37.

Zarsky, Lyuba. 1999. “Havens, Halos and Spaghetti: Untangling the Evidence about Foreign Direct Investment and the Environment.” *Foreign direct Investment and the Environment*, 13(8): 47–74.

Zhang, Kun, Zong-Yong Zhang, and Qiao-Mei Liang. 2017. “An Empirical Analysis of the Green Paradox in China: From the Perspective of Fiscal Decentralization.” *Energy Policy*, 103: 203–211.