Environmental Engineering and Management Journal August 2021, Vol. 20, No. 8, 1213-1223
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

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INFLUENCE OF DIFFERENT ENVIRONMENTAL INSTRUMENTS ON GREEN INNOVATION: EVIDENCE FROM 285 CITIES OF CHINA

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Abstract

Green innovation is the key measure to improve environmental efficiency and enhance environmental protection, but it is difficult to effectively drive green innovation only relying on the market mechanism. Therefore, exploring how to motivate green innovation through environmental instruments is essential for the sustainable development. Applying a spatial econometric model to panel data of 285 prefecture-level cities in China, this study estimates the dynamic impacts of the command and control and market-based instruments on green innovation, taking into account regional and innovation type heterogeneity. The results of the spatial econometric analysis show that the command and control instrument inhibits green innovation in the current period. Moreover, while the market-based instrument has no significant effect on green innovation in the current period, it significantly induces green innovation in the lagging period, which supports the Porter hypothesis. The sub-sample regression results reveal that the market-based instrument only induces green utility model which is less innovative both in the central and western regions. In addition, the market mechanism in the western regions should be improved. Finally, policy recommendations for the government are presented to improve China's environmental instrument system to promote green innovation. This study fills the gap in the literature by comparing the effects of command and control and market-based instruments, especially in developing countries.

Key words: command and control instrument, green innovation, market-based instrument, prefecture-level cities, spatial metrology

Received: December, 2019; Revised final: April, 2020; Accepted: May, 2020; Published in final edited form: August, 2021

1. Introduction

With the increasingly serious situation of resource exhaustion and pollution, environmental problems have become a major issue restricting sustainable economic development (Cai et al., 2017; Ramalingam et al., 2018). Entering the 13th Five-Year Plan period, China urgently needs to take a win-win path toward economic development and environmental protection. As an effective "transformation" innovation mode (Huisingh et al., 2015), green innovation is an important cornerstone of the Europe 2020 development strategy, an important engine to build a beautiful China, and a basic means for enterprises to gain competitive advantages given resource and environmental constraints (Lin et al., 2014: Tseng et al., 2013). In particular, the diffusion process of green innovation is the key to sustainable development. However, due to the characteristics of dual positive externalities (Rennings, 2000), promoting green innovation by relying solely on the market mechanism is difficult. To achieve sustainable development, many countries have set environmental standards or strict environmental instrument to reduce pollutant emissions and protect the environment (Horbach, 2008; Hojnik and Ruzzier, 2016). Since the 1970s, China has introduced a series of environmental instrument in different fields and links (Li and Lin, 2017). Currently, China's environmental instrument is evolving from a single command and control type to a multi-level environmental instrument system with command and control, market-based, and voluntary agreement-based instruments. With the economic growth slows down, innovation has become the engine

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of further growth (Yang and Yang, 2015). Therefore, it is significant to clarify the different impacts of different types of environmental instruments on green innovation in China (Shen et al., 2019) and explore how to promote green innovation, especially green innovation which is more innovative effectively through different instruments. In this paper, the impacts of the command and control instrument (CCI) and market-based instruments (MBI) on green innovation are mainly focused on.

Academically, the influence of environmental instruments on green innovation is a current research hotspot, with a large volume of research focused on the Porter hypothesis. From the static viewpoint, traditional economics held that environmental instruments will increase the "compliance cost" of enterprises and produce a "crowding-out effect" on enterprises' innovation behavior. Some scholars supported the negative effect of environmental instruments on technological innovation (Chintrakarn, 2008; Gollop and Robert, 1983; Greenstone et al., 2012; Wagner, 2007). Based on a dynamic understanding of competitive advantage, Porter and Van der Linde (1995) put forward the theory of "innovation compensation" in the form of the "Porter hypothesis." This hypothesis states that a properly designed environmental instrument can lead to innovation, compensate for the compliance cost of the environmental instrument, yield ecological benefits, and increase enterprise competitiveness. There are Porter hypothesis is divided into weak Porter hypothesis and strong Porter hypothesis. While the former indicates that environmental instruments can stimulate green innovation, the latter suggests that environmental instruments can not only stimulate green innovation, but also enhance the competitiveness of enterprises. Some scholars have revised Porter's "innovation compensation" theory. Schmutzler (2001) and Mohr (2002) used the principal–agent theory, bounded rationality, and spillover utility to find that environmental instruments can induce innovation that completely offsets the cost of implementation in very few cases. These theoretical differences have led to many empirical studies on the impacts of environmental instrument on green innovation. Arduini and Cesaroni (2001) employed the data of chemical industry in United States and Europe from 1993 to 1997, and found that the environmental instrument directly induces green innovation. Arimura et al. (2005), Brunnermeier and Cohen (2003) and Kammerer (2009) used the data of seven OECD countries, the United States and Germany respectively, and all drew the conclusion that environment regulations drive green innovation. The research of Berman and Bui (2001), Frondel et al. (2007), Jaffe and Palmer (1997), Kneller and Manderson (2012), Johnstone et al. (2010), Nelson et al. (1993), Popp (2003), and Rubashkina et al. (2015) also supported the "weak Porter hypothesis".

As deeper research, it has been found that there may not be simple linear relationship between environmental instrument and green innovation. Instead, more complex relationships such as a "U-shaped" relationship should be taken into consideration (Jiang et al., 2013). Based on China's provincial data, Ren et al. (2016) found an inverted "U" relationship between environmental instrument intensity and ecological efficiency. Zhang and Qu (2013) used a mathematical model to reveal an inverse W-type relationship between pollution tax, emission permit, unified emission standard, and green innovation. What's more, many scholars also paid attention to the impact of a single environmental instrument on enterprises' green innovation, focusing mainly on the effect of specific environmental instruments such as emission trading, environmental tax, and emission fees. Most of these scholars adopted the quasi-natural experiment method. However, testing single environmental instrument often fails to uncover the obvious effect of inducing green innovation. Villegas and Corina (2009) pointed out that emissions trading policies are not conducive to stimulating enterprises' green innovation. Calel and Dechezleprêtre (2016) used the patent data of enterprises from 18 countries in the European Union (EU) carbon trading system and found that the system played a very limited and consistent role in low-carbon technological innovation. A few foreign scholars compared the impact of different environmental instruments on innovation. For instance, Popp (2003) found that SO_2 emission trade is more effective than technical standards in improving the desulfurization technology, which indicated that MBI play a stronger role in innovation than the CCI.

As mentioned above, studies of the Porter hypothesis are yet to reach a consistent conclusion. Additionally, the literature mainly considers the environmental instrument and green innovation as a whole; few scholars have compared the different effects of CCI and MBI on different types of green innovation. As the largest developing country, the economic development levels, technological capabilities, science and technological policies, and other aspects across regions and provinces in China are differentiated. There are obvious regional characteristics and spatial agglomeration effects on green innovation. Compared to the eastern regions, the central and western regions are at an obvious disadvantage in green patent output. The spatial spillover of green innovation will obviously disturb the distinguishing of the actual effects of environmental regulations. However, current literature mostly uses the traditional econometric model, while neglects the spatial effects of environmental instruments on green innovation, which leads to a spatial correlation of observations.

In this study, the effects of both CCI and MBI on different types of green innovation are explored through spatial effects. By doing so, this study makes three contributions. First, the spatial relevance of environmental instruments in promoting green innovation is considered. Second, this study is based on a majority of China's 285 prefecture-level cities and thus, avoids the impact of biased sample selection on the estimation results. Third, patent data at the prefecture level in China is collected and methods of international standard are used to identify green patent information, which is conducive to examine the real effects of different environmental instruments on green innovation more accurately.

This paper is organized as follows. Section 2 and Section 3 introduces the research design and the variables of this study, respectively. Next, Section 4 presents empirical results and discussions from different dimensions. Finally, Section 5 concludes with relevant policy recommendations.

2. Research design

2.1. Spatial weight matrix selection

In constructing the weight matrix based on socioeconomic correlations, it is difficult to clearly avoid correlations with other variables in the model, which is a shortcoming of its application. The spillover of green innovation analyzed in this study refers mainly to the spillover to adjacent cities. Therefore, the spatial weight matrix is applied according to the adjacency criteria in terms of geographical characteristics.

The method of constructing the binary weight matrix W assumes that there are only one or two elements in the matrix, which is based upon whether sharing the border and is assumed as Luke-type. Here, 1 implies the two regions are interconnected and have transitive effects on each other, while 0 implies they are unrelated. Finally, the matrix is standardized such that the sum of its elements is 1.

2.2. Spatial econometric model

2.2.1. Global spatial autocorrelation test

Generally, the spatial autocorrelation of a spatial panel measurement model needs to be tested before it is established. At present, the global Moran's I index is the most widely used indicator for this purpose. It can be constructed as given by Eq. (1):

$$Moran'sI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(U_i-\bar{U}\right)\left(U_j-\bar{U}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(U_i-\bar{U}\right)^2} = \frac{n}{\sum_{i=1}^{n}\left(U_i-\bar{U}\right)^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(U_i-\bar{U}\right)\left(U_j-\bar{U}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{1}$$

Here,

$$\bar{U} = \frac{1}{n}\sum_{i=1}^{n}U_i$$

w_{ij} is the spatial weight matrix; U_i and U_j are the observed values of the variables in regions *i* and *j*, respectively; and *n* is the number of spatial units. The value of global *Moran's I* is between -1 and 1. The larger of the *Moran I* index, the more centralized distribution. What's more, the significance must be tested in order to ensure its accuracy after the computation.

2.2.2. Spatial model

At present, classical spatial econometric models include the spatial autoregression model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). The SAR is defined as expressed by Eq. (2):

$$y = \rho Wy + X\beta + \varepsilon, \varepsilon \sim N(0,\sigma^2 I_n), \tag{2}$$

where: y is the interpreted variable, W is the spatial weight matrix, ρ is the spatial autoregressive coefficient, X is a vector comprising the explanatory variables, β is the coefficient of explanatory variables, and ε is the normal random error vector.

Next, the SEM is defined as (Eq. 3):

$$y = X\beta + \mu, \mu = \lambda W\mu + \varepsilon \quad \ldots \quad \varepsilon \sim N(0,\sigma^2 I_n) \tag{3}$$

where: λ is the spatial error coefficient of the interpreted variable while other variables have the same meaning as in the SAR model.

Adding the spatial lagged terms of the explanatory variables to the SAR model yields the SDM. The corresponding regression equation is as follows (Eq. 4):

$$y = \rho Wy + X\beta + WX\gamma + \varepsilon \quad \ldots \quad \varepsilon \sim N(0,\sigma^2 I_n) \tag{4}$$

where: γ is a parameter representing exogenous interactions; all other variables are the same as in the SEM and SAR models.

Lagrange Multiplier (LM) tests are employed to choose the appropriate model. If the LM Lag term is more significant than the LM Error, and the Robust LM Lag is significant while the Robust LM Error is not significant, the SAR can be considered an appropriate model for the data; if the converse holds, then the SEM is considered to be more suitable. If, instead, all the terms are significant, SDM is suitable to estimate the coefficients. If all the terms are not significant, OLS model should be employed. The process of model selection is shown in Fig. 1.

In the model, natural logarithm of each variable is taken to eliminate heteroscedasticity. Since there is path dependence in technological innovation (Ruttan, 1997) and the impacts of environmental instruments may have a lag (Wang and Wang, 2011), the accumulation of early innovation as well as the impact of CCI and MBI on the current period are considered, and the model with one-period innovation and instrument variables is constructed.

3. Data

3.1. Sample and data

As China covers a vast territory, comparing the effects of environmental instruments on green innovation in different regions can better promote the improvement of regional environmental efficiency. This study selects prefecture-level cities of China as the preliminary sample and filters them according to the following criteria: (1) exclude prefecture-level cities that were established after 2008 and (2) exclude samples with missing data during the research period. Based on the above criteria, Tongren and Bijie cities in Guizhou, Danzhou and Sansha in Hainan, Hami and Turpan in Xinjiang, Haidong in Qinghai, and all cities in Tibet are eliminated; finally, 285 sample cities are obtained. It takes from one to three years for patents to go from the application to approval and publication stages; accordingly, the study's sample period is from 2008 to 2015.

Fig. 2 presents the spatial distribution of the prefectural-level cities explored in this paper.

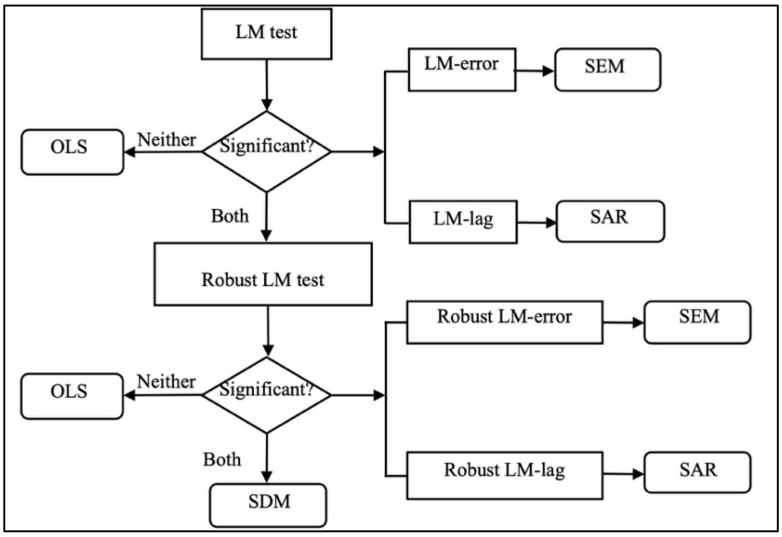

Fig. 1. Flow chart of model selection

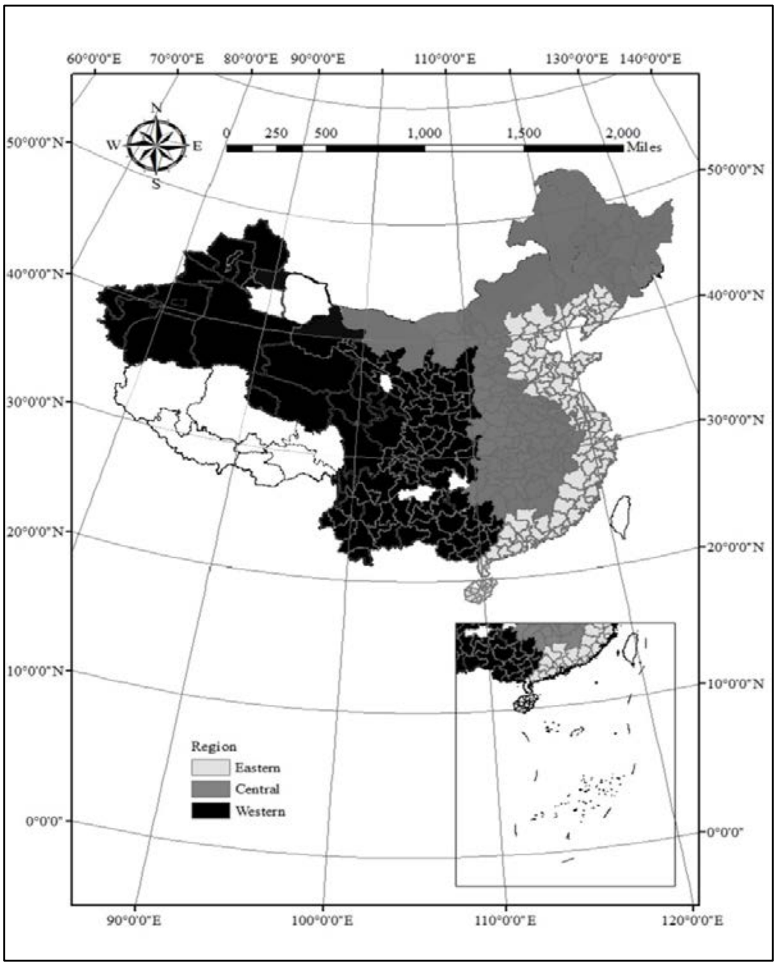

Fig. 2. The regional distribution of studying prefectural-level cities

In terms of data, as mentioned, the sample covers a time span from 2008 to 2015. The main data sources are as follows. The green innovation indicator is obtained from the Shanghai Intellectual Property (Patent Information) Public Service Platform Retrieval System (http://www.shanghaiip.cn/Search/login.do).

Measurement data of major pollutant emissions, foreign direct investment, gross industrial output, per capita gross domestic product (GDP), and local financial expenditure on science and technology of each prefecture-level city are derived from relevant China City Statistical Yearbooks (2009–2016). Data on pollution discharge fees are obtained from the China Environmental Yearbook.

3.2. Variable definitions

3.2.1. Green innovation

The Green List of International Patent Classification launched by the World Intellectual Property Organization identifies seven types of green patents. Accordingly, this study uses three types of green patents: waste management, energy conservation, and alternative energy production as indicators of green innovation, and calculates the annual number of green patents of the prefecture-level cities in China. Green invention patents and green utility models are further distinguished according to the degree of innovation contained in, and the former is higher than that in the latter. A total of 284,981 patents were reviewed in this study, yielding 255,247 patents after eliminating those that were applied for by foreign units and other prefecture-level cities. By matching 187,000 postcodes of all regions with the zip code on the patent contact address, the number of patents of each prefecture-level city can be obtained for each year.

3.2.2. Intensity of CCI

CCI are government administrative instruments, whereby the government imposes mandatory emission reduction targets and related standards on enterprises so as to limit their emissions. Existing research has mainly used the environmental governance investment (Brunnermeier and Cohen, 2003; Rubashkina et al., 2015) or pollution intensity (Domazlicky and Weber, 2004) to measure the intensity of the *CCI*. Based on the existing data, we learn from Li et al. (2019) and Ye et al. (2018), calculate the comprehensive index of pollutant emissions. Higher intensity of emissions indicates more stringent *CCI*. The comprehensive index of pollutant emissions is calculated mainly using the emissions of wastewater, sulfur dioxide (SO_2), and smoke per unit of industrial output in each year. The calculation procedure is as follows.

(1) Linear standardization of the emissions of different pollutants (Eq. 5)

$$UE_{ij}^{s} = \frac{\left[UE_{ij} - \min\left(UE_{j}\right)\right]}{\max\left(UE_{j}\right) - \min\left(UE_{j}\right)} \tag{5}$$

where: UE_{ij} indicates the emissions of the *j*-th pollutant per unit output of the *i*-th city, $max(UE_j)$ and $min(UE_j)$ indicate the maximum and minimum values of the *UE* across all cities in one year, respectively, and UE_{ij}^{s} represents the value after linear standardization.

(2) Calculation of the adjustment coefficients of pollutants (Eq. 6):

$$A_{ij} = UE_{ij} / \overline{UE_{j}} \tag{6}$$

The proportion of pollutants in different prefectural-level cities is different, and the emission intensity of different pollutants is also quite different. The adjustment coefficient A_{ij} represents the approximate characteristic difference among different pollutants and $\overline{UE_{j}}$ is the average level of the *j*-th pollutant per unit output in all prefectural-level cities during the sample period.

(3) Calculation of the *CCI* intensity (Eq. 7):

$$CCI_{i} = \frac{1}{3}\sum_{j=1}^{3} A_{ij} UE_{ij}^{s} \tag{7}$$

3.2.3. Intensity of MBI

MBI is mainly realized through taxes, fees, and emission permits. The Environmental Protection Law (Trial Implementation) of 1979 stipulated excessive pollution discharge fees should be levied in China. The policy has been implemented and remained relatively stable for many years. In consideration of the availability and reliability of the data, we select the pollution discharge fee of different prefectural-level cities per unit *GDP* as the agent variable. However, China has only announced a pollution discharge fee at the provincial level. In this paper, we suppose that a higher industrial output implies higher pollution discharge fees.

Therefore, we calculate the proportion of the industrial output of prefecture-level cities to the total industrial output of the whole province and multiply it with the total pollution discharge fee of that province to derive the pollution discharge fee data of each of its prefecture-level cities in that year, (Eq. 8):

$$MBR_{i} = \frac{IO_{i}}{IO_{P}} * PD_{P} / GDP_{i} \tag{8}$$

where: IO_i represents the industrial output of the i-th city, IO_P is the industrial output of the p-th province, which the i-th city belongs to. PD_P is the pollution discharge fee of the p-th province, GDP_i represents *GDP* of i-th city.

3.2.4. Control variables

Economic development level (ED): We use per capital *GDP* to measure the level of economic development and converse based on 2008 data. (2) Research and development level (RD): the per capita local financial expenditure on science and technology is adopted and then deflated by the 2008 *GDP* deflator index to represent this measure, since this variable can increase the overall research and development level of the city and further drive green innovation. (3) Foreign direct investment (FDI): The degree of economic openness is measured by the total amount of foreign direct investment. New technology and management with the entry of foreign direct investment may be absorbed by local enterprises and further stimulate innovation in undertaking regions.

4. Results and discussion

4.1. Analysis of regional differences in green innovation and environmental instruments

Fig. 3 shows that the total amount of green innovation in China is decreasing with the east, central, and west regions, and that the eastern region has absolute advantages in this regard. During the years 2008-2015, the total amount of green innovation in the eastern region has increased significantly while the central and western regions shows flatter growth.

Based on the means of each variable in Table 1, the eastern region has the highest level of green innovation aligned with its highest share of green invention patents; this is followed by the west and the central regions, in that order. The western region has the strongest intensity of the *CCI* and the smallest intensity of the MBI. This may potentially result from the strategy of "Developing the Western Region". Conversely, the eastern and central regions experience lower intensity of the *CCI* and stronger intensity of the MBI, which may be due to the high degree of marketization and low transaction costs. At a city level, based on the total number of green patents, Jingjin, Yangtze River Delta, Pan-Pearl River Delta, and Chengdu-Chongqing had high levels of green innovation in 2015. From the comprehensive index of pollutant emissions, it is seen that pollution is severe in western and central regions such as Heilongjiang, Ningxia, and Gansu, with a correspondingly strong intensity of the *CCI*. In addition, Chongqing, Yangtze River Delta, and Hebei experience the strongest intensity of the MBI according to the pollution discharge fee per unit GDP.

4.2. Global spatial autocorrelation test

Moran's I was used to test the spatial dependence of green innovation in 285 prefecture-level cities from 2008 to 2015 (Fig. 4). Based on the results, the spatial distribution of green innovation in 285 prefecture-level cities in China has obvious positive autocorrelation.

This implies that the spatial distribution of green innovation is not a random distribution, but a centralized distribution in areas with similar total green innovation levels. Areas with high green innovation have a near spatial trend, and areas with low green innovation are spatially adjacent to other low-green-innovation areas.

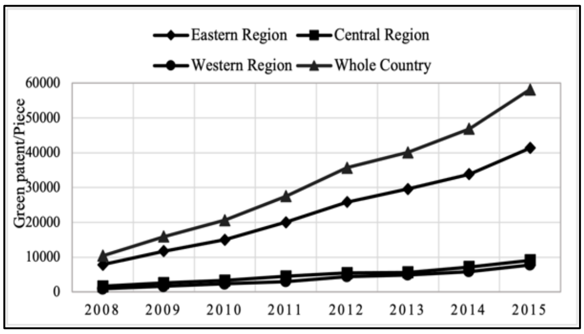

Fig. 3. The total amount of green innovation in China and its three regions from 2008 to 2015

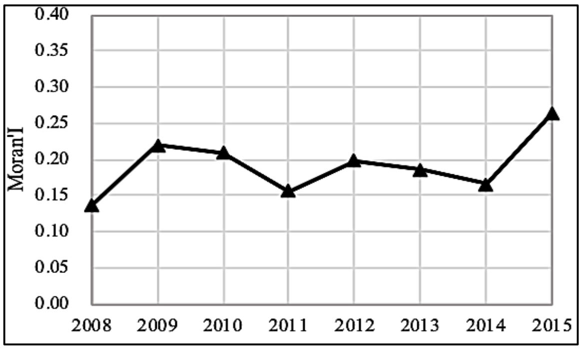

Fig. 4. Global spatial autocorrelation test results

4.3. Spatial panel model estimation results and discussion

Although the sample size based on prefectural-level cities of this paper is large (n=1995) to satisfy the asymptotic and unbiased estimation the normality of the data sample need to be considered (Ichinose et al., 2015).

However, the results of Jarque bera test show the non-normality of error distribution. Therefore, we use the maximum likelihood estimation developed by Shehata and Mickaiel (2013, 2014a, 2014b) which are suitable for the non-normal regression models in disturbance term. Stata 14.0 is used to estimate the effects of different environmental instruments on green innovation. The results are shown in Table 2.

The path dependence in technological innovation is obvious. On a nationwide basis, the *CCI* has significantly inhibited green innovation in the current period, and in the lagging period the effect is not significant. The negative effects may be a result of the costs of environmental instruments in the early implementation. Enhancing the *CCI* intensity will raise the cost of enterprises, which would crowd out enterprises' R&D investment.

Table 1. Descriptive statistics of variables from 2008 to 2015

Variables	***Eastern Region***			***Central Region***			***Western Region***		
	Mean	***Min***	***Max***	***Mean***	***Min***	***Max***	***Mean***	***Min***	***Max***
Patent/Term	229	0	7,683	49	0	1,088	46	0	1,931
Invention patent/Term	106	0	4,413	21	0	540	22	0	1,138
Utility model/Term	123	0	3,347	28	0	548	24	0	793
Comprehensive index of pollutant emissions	0.0635	0.000011	15.6813	0.2344	0.0002	29.5562	0.4699	0.000085	18.9378
Pollution discharge fee per unit *GDP*	0.2481	0.0087	1.2571	0.2551	0.0129	1.4807	0.2339	0.0201	1.8788
FDI/Ten thousand dollars	145,350.3	1,387.0	2,100,000	49,034.9	0	734,303	32,115.6	0	1,100,000
Per capital *GDP*/Yuan	35,313.83	10,050	109,044	21,548.25	6,455.27	94,546.3	21,657.7	3,602	136,429
Per capita local financial expenditure on science and technology/Yuan	114	5	1055	46	3	505	36	3	250

Table 2. Spatial panel model estimation results of total green innovation

Variable	***China***	***Eastern Region***	***Central Region***	***Western Region***
ln (*innovation_lag*)	0.6796*** (0.000)	0.8964*** (0.000)	0.6935*** (0.000)	0.3936*** (0.000)
ln (*CCI*)	-0.0469** (0.016)	-0.0338* (0.099)	-0.0141 (0.498)	-0.0107 (0.736)
ln (*CCI_lag*)	-0.0023 (0.904)	0.0223 (0.281)	-0.0163 (0.438)	-0.0004 (0.987)
ln (*MBI*)	-0.1171 (0.201)	-0.0816 (0.356)	-0.0700 (0.581)	0.1788 (0.284)
ln (*MBI_lag*)	0.3045*** (0.001)	0.1269 (0.154)	0.2036* (0.099)	0.2442 (0.142)
ln (*FDI*)	0.0306*** (0.000)	0.0260 (0.147)	0.0953*** (0.000)	0.0335*** (0.000)
ln (*ED*)	-0.0108*** (0.824)	0.0022 (0.934)	-0.0632 (0.262)	0.1037 (0.201)
ln (*RD*)	0.2690*** (0.000)	0.0810*** (0.001)	0.2323*** (0.000)	0.3615*** (0.000)
LM Error	1.4176 (0.233)	4.8519** (0.027)	1.0439 (0.306)	14.6014*** (0.001)
LM Lag	0.0151 (0.902)	0.1923 (0.661)	0.2733 (0.601)	36.2019*** (0.000)
LM Error (Robust)	310.6176*** (0.000)	4.6786** (0.030)	0.8084 (0.368)	174.9939*** (0.000)
LM Lag (Robust)	309.2151*** (0.000)	0.0190 (0.890)	0.0378 (0.845)	196.5944*** (0.000)
Model	OLS	SEM	OLS	SDM
Jarque Bera	59400***	519.7198***	7137.8124***	3371.4489***
Observations	1995	707	700	588

*Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. p values are shown in parentheses.*

Thus, the *CCI* plays a negative role in current green innovation. After the implementation of *CCI*, enterprises will adjust their production and the negative effect tends to drop off over time. However, the MBI imposes insignificant effect on current green innovation, while it can effectively stimulate green innovation in the lagging period. The insignificant influence of the MBI in the current period may mainly be due to the failure of effective market transmission. In the lagging period, the effect of the MBI on green innovation supports the Porter hypothesis. Based on the mechanism of environmental instruments inducing technological innovation, the premise that policies can be effectively transmitted to enterprises, imposing significant cost pressures or economic incentives on the latter, can be drawn.

As pursuers of profit maximization, when faced with a strict environmental instrument, enterprises will change, through green innovation, to reduce the cost and crowding-out effect brought about by environmental instruments. Improving production technology or promoting pollution control capabilities will eventually mitigate or offset the negative effects of environmental instruments on enterprises.

From the sub-samples perspective, it can be found that the *CCI* in the current period only inhibits green innovation in the eastern region. The role of the *CCI* in the central and western regions is not obvious, which may be resulted from the inappropriate and inadequate monitoring. Next, the MBI has no significant effect on current green innovation for all regions. In the lagging period, the MBI promotes green innovation only in the central region. According to the MBI mechanism, the effect of the instrument should increase exogenous energy prices. Marketization of energy prices is the condition for the effective transmission of MBI (Cullen and Mansur, 2014; Pettersson et al., 2012). The western region is located in the inland and is far from the economic development center, the insignificant effect of MBI on green innovation may be resulted from its incomplete market mechanism.

Although the market is more lively and effective in the eastern region, there are less industries with high energy consumption and its energy consumption such as coal, oil and electricity is smaller, which is less affected by the fluctuation of energy prices. The collection of pollution discharge fees has not formed an effective backward effect on green innovation.

Table 3. Spatial panel model estimation results of green innovation patents

Variable	*China*	*Eastern Region*	*Central Region*	*Western Region*
ln (*ip_lag*)	0.4739*** (0.000)	0.7669*** (0.000)	0.4928*** (0.000)	0.3298*** (0.000)
ln (*CCI*)	0.0031 (0.872)	-0.0754** (0.037)	-0.0754 (0.037)	-0.0138 (0.690)
ln (*CCI_lag*)	-0.0290 (0.133)	0.0746** (0.040)	0.0746 (0.040)	0.0165 (0.625)
ln (*MBI*)	0.1712 (0.102)	-0.2389 (0.134)	-0.1060 (0.515)	0.2337 (0.205)
ln (*MBI_lag*)	0.1815* (0.084)	0.3942** (0.015)	0.2258 (0.157)	0.2978 (0.105)
ln (*FDI*)	0.0422*** (0.000)	0.0994*** (0.002)	0.1473*** (0.000)	0.0382*** (0.000)
ln (*ED*)	0.1036** (0.030)	0.1542 (0.296)	0.1056 (0.161)	-0.0298 (0.741)
ln (*RD*)	0.3938*** (0.000)	0.1225** (0.013)	0.2839*** (0.000)	0.4177*** (0.000)
LM Error	5.2983** (0.021)	2.4229 (0.119)	2.3654 (0.124)	4.0803** (0.043)
LM Lag	34.4909*** (0.000)	1.6570 (0.198)	5.4168** (0.019)	21.9172*** (0.000)
LM Error (Robust)	435.8561*** (0.595)	1.5565 (0.212)	0.2244 (0.635)	207.3276*** (0.000)
LM Lag (Robust)	465.0487*** (0.001)	0.7906 (0.373)	3.2758* (0.070)	225.1645*** (0.000)
Model	SDM	OLS	SAR	SDM
Jarque Bera	22600***	50700***	15500***	1321.8286***
Observations	1995	707	700	588

*Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. p values are shown in parentheses.*

Table 4. Spatial panel model estimation results of the green utility model

Variable	*China*	*Eastern Region*	*Central Region*	*Western Region*
ln (*um_lag*)	0.4571*** (0.000)	0.7798*** (0.000)	0.5779*** (0.000)	0.3042*** (0.000)
ln (*CCI*)	0.0169 (0.316)	-0.0646** (0.030)	-0.0219 (0.338)	0.0365 (0.258)
ln (*CCI_lag*)	-0.0350** (0.037)	0.0494* (0.099)	-0.0080 (0.727)	-0.0344 (0.277)
ln (*MBI*)	0.1852** (0.042)	-0.2059 (0.117)	-0.1516 (0.315)	0.3190* (0.061)
ln (*MBI_lag*)	0.1203 (0.189)	0.3235** (0.015)	0.3348** (0.024)	0.1451 (0.392)
ln (*FDI*)	0.0313*** (0.000)	0.0382 (0.147)	0.0928*** (0.000)	0.0262*** (0.004)
ln (*ED*)	0.2168*** (0.000)	0.1143 (0.162)	-0.0878** (0.005)	0.1435* (0.085)
ln (*RD*)	0.3663*** (0.000)	0.1277*** (0.002)	0.2902*** (0.000)	0.4274*** (0.000)
LM Error	75.5998*** (0.000)	0.2582 (0.611)	11.9404*** (0.000)	40.8064*** (0.000)
LM Lag	105.4051*** (0.000)	0.2329 (0.629)	3.3380* (0.067)	63.6091*** (0.000)
LM Error (Robust)	37.5997*** (0.000)	0.0909 (0.763)	9.3159*** (0.002)	161.6680*** (0.000)
LM Lag (Robust)	67.4050*** (0.000)	0.0656 (0.797)	0.7135 (0.398)	184.4707*** (0.000)
Model	SDM	OLS	SEM	SDM
Jarque Bera	33500***	39.3989***	1419.5912***	1216.2830***
Observations	1995	707	700	588

*Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. p values are shown in parentheses.*

Considering the degree of innovation, we model sub-sample regressions of green invention patents and the green utility model (Tables 3-4, respectively) and obtain interesting results. From the above analysis, the MBI have no significant effect on green innovation both in the current and lagging periods in the central region; however, it has significant promotion on the green utility model in the central region in the lagging period. In addition, MBI drives the green utility model in the western region in the current period. This may be because of the rent-seeking behavior in central and western regions: government only pursues the number of innovation while neglects the quality in order to achieve political achievements, which leads to a crowding-out effect on green invention patents. In addition, *RD* and *FDI* both promote green innovation, with the promoting effect of *RD* is significantly greater. While *ED* has a negative effect on green innovation, this may result from the "only *GDP* theory" whereby the excessive pursuit of *GDP* by local officials will be detrimental to green innovation.

From the results of the sub-sample regressions, the positive effect of *FDI* on green innovation in central regions is highest, while *RD*'s effect is most prominent in the western region. Moreover, *RD* plays a more important role in green innovation patents than in the green utility model.

5. Conclusions

Green innovation is of great importance for sustainable development in China. Due to the failure of the market mechanism in deciding the enterprises' green innovation behavior, many countries have adopted a variety of environmental instruments.

China is experiencing a change of pace in economic growth; hence, it is essential to clarify the effects of environmental instruments on green innovation and perfect the environmental instrument system. In this study, prefecture-level city samples are examined, and a spatial metrology model is proposed to estimate the effects of the *CCI* and MBI on green innovation, taking into account both regional and innovation type heterogeneity. The model includes one-period lagged innovation and environmental instrument variables.

The results of this study are as follows:

➢ From the national viewpoint, the CCI inhibits current green innovation while has no significant effect in the lagging period. The impact of the MBI in the current period is not significant, but it can obviously stimulate green innovation in the lagging period, which supports the Porter hypothesis.

➢ Through regional estimations, it is found that the CCI only plays an obvious role in the eastern region, while the MBI only promotes the green innovation of the central region.

➢ Moreover, analysis of different innovation types thrown up some intriguing results. The MBI only induce green innovation with lower innovation level while do not affect green innovation with high innovation level significantly both in the central and western regions.

➢ From the results of the control variables, we find that RD and FDI can obviously promote green innovation. However, the ED level inhibits green innovation. RD is most effective in the western region while FDI is significantly more effective in the central regions.

Based on these empirical results, we can draw the following policy implications:

● ***Promote market-based transformation of environmental instrument tools***

The MBI is better than the *CCI* in driving green innovation. As such, China should gradually promote the transformation of its environmental instruments system and realize the key role of the market mechanism in promoting green innovation and impelling the green transformation of enterprises. In addition, China should create an improved and unified national carbon emission trading market through pilot projects of emission trading, and further build a trading mechanism that is suitable for green innovation.

● ***Strengthen the guidance of high green innovation***

Government should pay attention to the differences in innovation categories and strengthen the guidance of high green innovation, that is, green invention patents. Specifically, the government should boost its science and technology budget, increase innovation subsidies, and build up regular evaluation on the effectiveness of innovation to prevent rent-seeking behavior.

● ***Perfect the environmental instrument system with targeted and spatial differences***

In the central and western regions, the government should strengthen its policy supervision, establish an open and clear review mechanism, and enhance the punishment mechanism to reduce rent-seeking behavior. Moreover, in the western region, the government should focus on perfecting the market mechanism, reduce market-distorting behaviors such as price protection, and fully enlarge the innovation driving effect of the MBI.

● ***Improve the construction of an external support system for green innovation***

The government should increase investment in green innovation and development, realize the leveraging role of government funds, and broaden the financing channels of technology funds, especially in the western region. Optimizing the business environment and paying attention to the quality of FDI are conducive for green innovation promotion, especially in the central and western regions. In addition, while pursuing economic growth, we should also pay attention to improving the quality and level of *ED*.

Nonetheless, this study has some limitations. Firstly, given the availability of data at the prefecture level, the choice of agent variables for environmental instruments is limited. With increasingly more urban statistical data to be released in the future, the proxy variables used in this study can be improved upon to enhance model robustness. Secondly, only the type and quantity of green patents (green invention patent and green utility model) are employed to measure the green innovation in cities is too one-sided to further identify green innovation that is more conducive to sustainable development. In the future, the screening of the quality of green patents should be further refined. Finally, the impact of environmental instruments on green innovation can be further analyzed from an urban agglomeration view so as to promote the construction of an ecological civilization and facilitate green economic transformation in China.

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