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Effects of Environmental Regulations on Technological Innovation Efficiency in China's Industrial Enterprises: A Spatial Analysis

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Received: 19 February 2019; Accepted: 5 April 2019; Published: 11 April 2019

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Abstract: China's traditional industrial model is characterized by high energy consumption and high pollution, which results in many environmental problems that cannot be ignored. To achieve sustainable development, the Chinese government has proposed five development concepts of "innovation, coordination, green, openness, and sharing". This initiative highlights the urgency of China's efforts to strengthen environmental regulation. Based on the panel data of industrial enterprises in China from 2006 to 2015, this study not only investigates the spatial features of technological innovation efficiency, but also examines the relationship between technology innovation efficiency and environmental regulations from a spatial perspective. The results indicate that first, China's provincial-level technological innovation efficiencies are uneven in space. Second, voluntary regulation positively affects the technological innovation efficiency of industrial enterprises at the provincial level, while mandatory regulation has no significant impact. Third, there is a spatial spillover effect in voluntary regulation at the provincial level. One highlight implication is that the government should promulgate environmental regulations based on each province's technological innovation potential, due to the spatial differences in technological innovation activities.

Keywords: environmental regulations; technological innovation efficiency; spatial econometric model; China

1. Introduction

With the emergence of the Porter Hypothesis, the relationship between environmental regulations (ERs) and technological innovation has received wide attention from researchers over the last two decades [1–3]. To investigate the role of regulation, scholars have carried out a great deal of studies, upon which no consensus has been reached yet, as scholars continue to find conflicting evidence [4–6]. New research has also emerged investigating the indirect effects of ERs on technological innovation [7]. However, these studies have typically ignored the spatial agglomeration of technological innovation activities. The purpose of this study is to examine whether ERs affect technological innovation efficiency at the provincial level from the viewpoint of geography.

Figure 1a–d details the spatial disparity of technological innovation activities in Chinese industrial enterprises for the year 2015. To be specific, provinces with high innovation inputs (i.e., R&D personnel—research and development personnel—and R&D expenditure) are mainly concentrated in eastern China; provinces with high innovation outputs (i.e., the number of patent applications and new product sales revenue) are also predominantly concentrated in eastern China. Overall, from the perspective of geography, there is a spatial agglomeration in Chinese technological innovation activities. Therefore, spatial location should be taken into consideration when examining the relationship between technological innovation and ERs.

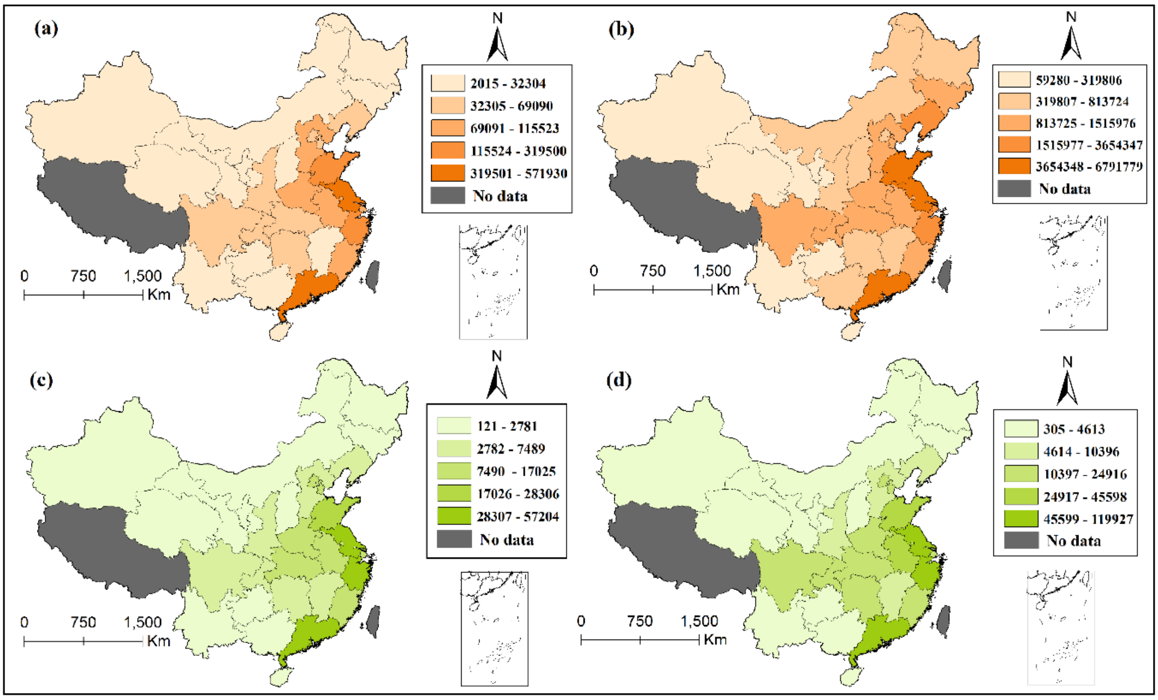


Figure 1. Innovation inputs and innovation outputs, 2015. (**a**) R&D personnel. (**b**) R&D expenditure. (**c**) New product sales revenue. (**d**) The number of patent applications. The Figures are drawn by ArcGIS 10.3.

Taking a cue from Figure 1, the panel data of China's 30 provinces is used to explore the relationship between ERs and technological innovation through spatial econometric methods. In contrast to traditional econometric methods, spatial econometric methods can investigate whether technological innovation is affected by the ERs of adjacent areas. Furthermore, the development of technological innovation in Chinese industrial enterprises is measured by an improved data envelopment analysis (DEA) model. To the best of our knowledge, no study to date has explored the Porter Hypothesis by combining the DEA model and spatial econometric model.

As a result, the contributions of this study have the following four aspects. First, this study applies three methodologies—statistical, spatial, and visual—to examine the relationship between technology innovation efficiency and ERs, which may develop a bridge between the geography of innovation and the ecological-economic literatures, and thus is one of the major contributions of this study. Second, this study considers the spatial agglomeration of technological innovation activities when examining the Porter Hypothesis, which will extend the literature on the Porter Hypothesis to geography. Third, for all we know, this study is the first empirical measurement of technological innovation efficiency through the game cross-efficiency DEA model. There are two reasons for using this model: (1) In the traditional DEA model, if the decision-making units (DMUs) are effective, their efficiency scores are 1, which leads to unavailable discrimination of the DMUs. (2) The improved cross-efficiency DEA model takes into account the game relationship between DMUs. Fourth, fully considering the spatial agglomeration of technological innovation efficiency at the provincial level, spatial econometric methods are used to test the Porter Hypothesis; these methods may avoid the estimation bias due to ignoring spatial effects.

The structure of this study is as follows. Section 2 provides literature review. Section 3 presents the improved cross-efficiency DEA model and the spatial econometric methods. Sections 4 and 5 discuss the relationship between ERs and technological innovation efficiency.

2. Literature Review

2.1. Agglomeration and Technological Innovation

Agglomeration theory argues that innovative activities generally take place inside industrial clusters [8]. The theory of traditional Marshallian externalities argues that innovation activities are characterized by concentration, which is more evident than production [9]. Investigating the location of more than 1000 R&D labs, Carlino et al. [10] found that R&D activities are substantially more concentrated than manufacturing. Moreover, the 'natural advantages' of a region, such as education, economic development, and unique culture, promote innovation activities to be carried out first in some industrial enterprises, which induces varying degrees of innovation poles [11]. Taking a geographical view on creative industries, Boix et al. [12] found that creative firms are highly clustered in space, and result in a 'creative belt'. Jang and Kim [13] investigated the effects of firms' agglomeration on product innovation in local districts, and they revealed that geospatial locations play an important role in stimulating product innovation among co-located firms.

In general, the latest knowledge about science and technology is valuable in a short time, and the reciprocal exchange of information among geographically adjacent enterprises carried out innovation activities can reduce some risks [14]. There is evidence that geographic proximity is important for localized knowledge spillovers in innovation activities. For example, Drivas and Economidou [15] investigated the impact of agglomeration on patents, and they found that knowledge spillovers would take place in states with geographical proximity. Using a meta-analytic regression, Neves and Sequeira [16] found that there is a significant spillover effect in the production of knowledge.

2.2. The Porter Hypothesis

ERs play an indispensable role in controlling the harmful effects of economic activities on the ecological environment; nevertheless, they impose an environmental cost on industrial enterprises [5,7]. The conventional wisdom concerning ERs is that although regulations are desirable in terms of a broader social perspective, they would be detrimental to the enterprises, as enterprises are under pressure to internalize additional cost that had antecedently been disregard [17].

To explore the seemingly contradictory relationship between ERs and technological innovation, numerous researchers have shed light on the statement of Porter [18], who argued that ERs can trigger technological changes and facilitate technological innovation, thus offsetting the losses caused by ERs. Porter and van der Linde [19] further developed this argument, and emphasized that ERs, if well designed, may result in cost-saving technological innovation that exceed environmental costs. This statement came to be regarded as the Porter Hypothesis.

The existing literature regarding the Porter Hypothesis provides very mixed results both theoretically and empirically. Some researchers conclude that the Porter Hypothesis is established. Jaffe and Palmer [3] argued that if the influence of unobserved specific-industries is controlled, ERs may have a significant positive impact on corporate R&D expenditures. Based on a bottom-up view of regulation, Ford and Steen [20] investigated Australian oil and gas industry, and revealed that various technological innovations are related to a high compliance burden. Taking upstream companies as an example, Chakraborty and Chatterjee [7] confirmed that there is a significant increase in innovation expenditure in response to foreign ERs.

Some researchers detect a negative impact, especially for pollution-intensive industries. Using Census data for individual paper mills, Gray and Shadbegian [21] argued that environmental investment is likely to crowd out productive investment. Nath [22] found that ERs would discourage technological innovation in light of UK industrial sector. Some researchers uncover no discernible relationship. Kneller and Manderson [23] found that pollution abatement pressure can stimulate environmental investment, whereas there is no evidence that ERs can always have a positive effect on the R&D of industrial enterprises.

It is useful to note that most of the previous studies believe that technological innovation activities are homogeneous in space. However, China's technological innovation activities are characterized by spatial agglomeration (see Figure 1), which means that examining the Porter Hypothesis at the provincial level needs to consider the spatial effects. To the best of our knowledge, there are few assessments, and only a few exceptions that indirectly examine the issue. This study aims to extend the literature through investigating relationship between ERs and technology innovation efficiency from the viewpoint of geography.

3. Data and Methods

3.1. Variables and Data Sources

3.1.1. Dependent Variable

The efficiency of technology innovation (TIE) in industrial enterprise is taken as the dependent variable. The existing literature typically uses the number of patent applications as the desirable output of technological innovation [23–26]. However, some researchers had questioned this practice, and suggested that not all innovations are patentable [27]. Based on the innovation value chain, technological innovation can be regarded as two stages: knowledge innovation and product innovation. Therefore, the number of patent applications (NPA) and the sales revenue of new products for industrial enterprises (NPIE) are used as the desirable outputs [28]. The inputs included the R&D personnel of industrial enterprises (PIE), the R&D expenditure of industrial enterprises (EIE), and the equipment of R&D institutions (EIN). The undesirable outputs consisted of three types of industrial pollution, namely solid waste (ISW), waste gas (IWG), and wastewater (IWW). The data on the desirable outputs and the inputs are collected from China's Statistics Yearbook on Science and Technology Activities of Industrial Enterprises. The data on the industrial waste gas and the wastewater are obtained from China Environmental Yearbook. The data on the industrial solid waste are derived from China Statistical Yearbook.

3.1.2. Independent Variable

The design of ERs is of crucial importance to examine the Porter Hypothesis. According to Majumdar and Tosun [29,30], ERs were divided into two types: flexible and inflexible. Flexible regulation characterized by little administrative control encourages industrial enterprises to develop appropriate processes to meet environmental standards, while inflexible regulation combines powerful administrative control with little incentive [5]. Following Majumdar and Marcus [29], ERs are classified as voluntary and mandatory in this paper.

(1) Voluntary regulation

Voluntary regulation means that the government supervises the production activities of industrial enterprises to prevent them from deviating from environmental standards. That is, if a province strengthens voluntary regulation, the pressure on its industrial enterprises for technological innovation will increase. The number of environmental protection agencies (NOEPA) is used as an indicator for voluntary regulation [31], and relevant data are obtained from China Environmental Yearbook.

(2) Mandatory regulation

Mandatory regulation is that the government regulates the production activities of industrial enterprises with administrative penalties to achieve "friendly innovation", and its chief characteristic is compulsory [31–33]. That is, if an industrial enterprise violates environmental standards, it will be punished by the government. The number of environmental administrative punishment cases (NOEAPC) is used as an indicator for mandatory regulation, and relevant data are obtained from China Environmental Yearbook.

3.1.3. Control Variables

In addition to the R&D inputs and ERs, there are many factors that affect technological innovation efficiency in China's provincial industrial enterprises. Based on previous studies, four control variables are taken into consideration, namely government support, foreign investment, economic development, and environmental pollution [7,33].

(1) Government support

Innovation activities are characterized by the low rate of technology transfer, which results in high opportunity costs for industrial enterprises. As such, appropriate support provided by the government to industrial enterprises, may reduce opportunity costs. The government's financial support for R&D (GFS) in industrial enterprises is taken as the proxy for government support, and relevant data are collected from China's Statistics Yearbook on Science and Technology Activities of Industrial Enterprises.

(2) Foreign investment

Foreign investment can supply industrial enterprises with funds and advanced technology, which is conducive to promoting technological innovation. The actual use of foreign investment (AUOFI) is taken as the proxy for foreign investment, and relevant data are derived from China Statistical Yearbook.

(3) Economic development

The level of economic development in a province affects its ability to innovate. If a province has good economic development, it will have the advantage of innovative resources. The gross domestic product (GDP) is taken as the proxy for economic development, and relevant data are collected from China Statistical Yearbook.

(4) Environmental pollution

If the environmental pollution of a province is more serious, the government is more likely to adopt ERs. The environmental pollution is represented by calculating the total amount of carbon emissions (CO_2), and relevant data are obtained from China Environmental Yearbook.

It is essential to consider time lags when analyzing innovation activities. Following Chen and Hong [28,34], we set a one-year lag for the technological innovation process. The panel dataset covering 30 provinces in China from 2006 to 2015 is constructed (due to the missing of data, Tibet, Hong Kong, Macau, and Taiwan are not included). The descriptive statistics of the panel data are shown in Appendix A. The cumulative amount of the R&D equipment is calculated using the perpetual inventory method with a depreciation rate of 10%. Taking into account inflation, the NPIE, EIE, EIN, GFS, and AUOFI are converted into 2006 constant prices with their deflators. In addition, all indicators are standardized.

3.2. Methods

3.2.1. Model for Calculation of Technological Innovation Efficiency

As a non-parametric statistical method for efficiency evaluation, DEA can effectively deal with the relative efficiency of complex systems with multiple inputs and outputs, so it has been widely used in the evaluation of DMUs [35–37]. However, the optimal solution of the traditional DEA model is likely to be unique, so the traditional DEA model is not suitable to discern the spatial differences of DMUs. To solve this problem, a game cross-efficiency model is constructed. The basic idea of the game cross-efficiency model is to maximize the efficiency scores of competitors in the case of maintaining own efficiency scores [38].

The efficiency of technological innovation in industrial enterprises is evaluated at the province-level, so each province can be regarded as a DMU. Suppose there are n DMU_j (j = 1, 2, 3, ... , n) with m inputs I_{ij} (i = 1, 2, 3, ... , m) and s outputs O_{rj} (r = 1, 2, 3, ... , s). Following Cheng [38], the game cross-efficiency model is defined by Formula (1):

$$\alpha_{dj} = \sum_{r=1}^{s} u_{rj}^{d} O_{rj} / \sum_{i=1}^{m} v_{ij}^{d} I_{ij} \tag{1}$$

where u_{rj}^d and v_{ij}^d are the practicable weights of O_{rj} and I_{ij}, respectively. The values of u_{rj}^d and v_{ij}^d are obtained by the following set of linear programming (2).

$$\begin{aligned} &\alpha_{dj} = \max \sum_{r=1}^{s} u_{rj}^{d} O_{rj} \\ &s.t. \begin{cases} \sum\limits_{r=1}^{s} u_{rj}^{d} O_{rj} - \sum\limits_{i=1}^{m} v_{ij}^{d} I_{ij} \le 0; \ \sum\limits_{i=1}^{m} v_{ij}^{d} I_{ij} = 1; \ \alpha_d \times \sum\limits_{i=1}^{m} v_{ij}^{d} I_{id} - \sum\limits_{r=1}^{s} u_{rj}^{d} O_{rd} \le 0; \\ u_{rj}^{d}, v_{ij}^{d} \ge \varepsilon; \ r = 1,2,3,\ldots,s; \ i = 1,2,3,\ldots,m \end{cases} \end{aligned} \tag{2}$$

where α_d is a parameter whose initial value is calculated by the traditional cross-efficiency model. Then the value of the average game cross-efficiency is calculated by Formula (3):

$$\theta_j^* = \frac{1}{n} \sum_{d=1}^{n} \alpha_{dj} = \frac{1}{n} \sum_{d=1}^{n} \sum_{r=1}^{s} u_{rj}^{d*}(\alpha_d) O_{rj} \tag{3}$$

In addition to new products, it is also important to consider the outputs that are not conducive to the environment. Scheel [39] classified DEA methods with undesirable outputs as direct and indirect methods, and the basic idea of the indirect methods is to transfer undesirable outputs into "desirable outputs" by constructing a monotonically decreasing function f [40,41]. Following the indirect methods, the conversion function $f(U) = -U$ is constructed. Decreasing "desirable outputs" transformed by the conversion function means increasing original undesirable outputs. The game cross-efficiency model under environmental constraints is constructed by Formula (4):

$$\begin{aligned} &\max \sum_{r=1}^{s} u_{rj}^{d} O_{rj} - \sum_{k=1}^{q} \omega_{kj}^{d} Z_{kj} \\ &s.t. \begin{cases} (\sum\limits_{r=1}^{s} u_{rj}^{d} O_{rj} - \sum\limits_{k=1}^{q} \omega_{kj}^{d} Z_{kj}) - \sum\limits_{i=1}^{m} v_{ij}^{d} I_{ij} \le 0; \ \alpha_d \times \sum\limits_{i=1}^{m} v_{ij}^{d} I_{id} - (\sum\limits_{r=1}^{s} u_{rj}^{d} O_{rd} - \sum\limits_{k=1}^{q} \omega_{kj}^{d} Z_{kd}) \le 0 \\ \sum\limits_{i=1}^{m} v_{ij}^{d} I_{ij} = 1; \ u_{rj}^{d}, v_{ij}^{d}, \omega_{kj}^{d} \ge 0; \ r = 1,2,3,\ldots,s; \ i = 1,2,3,\ldots,m; \ k = 1,2,\ldots,q \end{cases} \\ &\alpha_{dj} = (\sum_{r=1}^{s} u_{rj}^{d} O_{rj} - \sum_{k=1}^{q} \omega_{kj}^{d} Z_{kj}) / \sum_{i=1}^{m} v_{ij}^{d} I_{ij}; \\ &\theta_j^* = \frac{1}{n} \sum_{d=1}^{n} \alpha_{dj} = \frac{1}{n} \sum_{d=1}^{n} (\sum_{r=1}^{s} u_{rj}^{d*}(\alpha_d) O_{rj} - \sum_{k=1}^{q} \omega_{kj}^{d*}(\alpha_d) Z_{kj}) \end{aligned} \tag{4}$$

where Z_{kj} $(k = 1,2,\ldots,q;\ j = 1,2,\ldots,n)$ represents undesired output; ω_{kj}^d is the feasible weight of Z_{kj}; the definition of other variables is consistent with the Formulas (1)–(3).

3.2.2. Model for Test of Spatial Dependence

Spatial autocorrelation, also known as the Moran index (*Moran's I*), refers to the degree of association between adjacent regions [42–44]. Before using spatial econometric methods, a spatial autocorrelation model needed to be constructed to examine whether China's province-level technological innovation efficiency have spatial dependence. To do this, the *Moran's I* test is conducted by Formula (5):

$$MI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij})\sum_{i}^{n}(X_i - \overline{X})^2} \tag{5}$$

where $\overline{X} = 1/n\sum_{i=1}^{n} X_i$, which represents the mean of X_i; X_i and X_j represent the technological innovation efficiency of provinces i and j, respectively; n is the number of spatial units; W_{ij} represents the spatial weight matrix. It can be seen from Formula (5) that *Moran's I* ranges from −1 to 1. If $MI > 0$, which indicates that there is a positive spatial autocorrelation on the efficiency of technological innovation. If $MI < 0$, which indicates that there is a negative spatial autocorrelation on the efficiency of technological innovation.

According to Formula (5), the design of spatial weight matrix W_{ij} is of crucial importance to the spatial autocorrelation model. The existing literature on spatial autocorrelation mostly uses a single weight matrix. We construct three spatial weight matrices, namely adjacent matrix, geospatial distance matrix, and economic distance matrix.

The first is the adjacent matrix, which reflects the spatial relationship of adjacent provinces, and it is constructed by Formula (6):

$$W_{ij}^{A} = \begin{cases} 1 & \text{if provinces } i \text{ and } j \text{ are adiacent} \\ 0 & \text{if provinces } i \text{ and } j \text{ are not adiacent} \end{cases} \tag{6}$$

The second is the geospatial distance matrix, which measures geospatial proximity among provinces, and it is constructed by Formula (7):

$$W_{ij}^{s} = \begin{cases} \frac{1}{d^2{}_{ij}} & (i \neq j) \\ 0 & (i = j) \end{cases} \tag{7}$$

where d_{ij} calculated by latitude and longitude represents the geospatial distance between provinces i and j.

The third is the economic distance matrix, which measures economic proximity among the provinces. In other words, the economic distance reflects the gap in economic development among the provinces, and it is constructed by Formula (8):

$$W_{ij}^{E} = \begin{cases} \frac{1}{\left|\overline{Y_i} - \overline{Y_j}\right|} & (i \neq j) \\ 0 & (i = j) \end{cases} \tag{8}$$

where Y_i is the average value of per capita GDP of province i.

3.2.3. Spatial Panel Econometric Model

Spatial panel econometric model is divided into three types, namely, spatial panel lag model (SPLM), spatial panel error model (SPEM), and spatial panel Dubin model (SPDM) [45,46]. Specifically, if the spatial dependence exists in the dependent variable, it is the SPLM; if the spatial dependence exists in the error term, it is the SPEM; if the spatial dependence exists in the independent and dependent variables, it is the SPDM. Based on previous studies [45,46], the panel ordinary least squares (POLS) model is first constructed as follows:

$$TIE_{it} = \alpha_i + \beta X_{it} + e_{it} \tag{9}$$

where α_i is a constant term; X_{it} represents the set of independent variables; e_{it} denotes the error term.

We add individual effect u_i and time effect v_t to the Formula (9), constructing the traditional panel econometric model as follows:

$$TIE_{it} = \beta X_{it} + e_{it} + u_i + v_t \tag{10}$$

We choose the economic distance matrix $W^E{}_{ij}$ to construct the spatial econometric model. The $W^E{}_{ij}$ is incorporated into the dependent variable of model (10) to construct the SPLM as follows:

$$TIE_{it} = \alpha_i + \beta X_{it} + \rho \sum_{j=1}^{n} W_{ij}^{E} TIE_{jt} + e_{it} + u_i + v_t \tag{11}$$

where ρ is the coefficient of $\sum_{j=1}^{n} W_{ij}^{E} TIE_{jt}$, indicating the spatial spillover effect of the efficiency of technology innovation.

The $W^E{}_{ij}$ is added to the error term of model (10) to construct the SPEM as follows:

$$TIE_{it} = \alpha_i + \beta X_{it} + \lambda \sum_{j=1}^{n} W_{ij}^{E} \phi_{jt} + e_{it} + u_i + v_t \tag{12}$$

where λ is the coefficient of $\sum_{j=1}^{n} W_{ij}^{E} \phi_{jt}$, and φ is the spatial autocorrelation error term.

The $W^E{}_{ij}$ is incorporated into the independent and dependent variables of model (10) to construct the SPDM as follows:

$$TIE_{it} = \alpha_i + \beta X_{it} + \rho \sum_{j=1}^{n} W_{ij}^{E} TIE_{jt} + \delta \sum_{j=1}^{n} W_{ij}^{E} X_{jt} + e_{it} + u_i + v_t \tag{13}$$

where δ is the coefficient of $\sum_{j=1}^{n} W_{ij}^{E} X_{jt}$, indicating the spatial spillover effect of the ERs, and other variables have the same meaning as Formula (11).

4. Results

4.1. Technological Innovation Efficiency

The game cross-efficiency model is used to calculate China's province-level technological innovation efficiencies from 2006 to 2015. As shown in Table 1, the results demonstrate that the game cross-efficiency model performs well in differentiating the DMUs.

Table 1. Results of technological innovation efficiencies from 2006 to 2015.

DMU	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Mean
Zhejiang	0.783	0.971	0.950	0.953	0.946	0.898	0.792	0.892	0.711	0.739	0.864
Tianjin	0.824	0.816	0.826	0.854	0.839	0.856	0.885	0.879	0.884	0.881	0.855
Chongqing	0.825	0.905	0.837	0.865	0.731	0.635	0.809	0.906	0.882	0.883	0.828
Shanghai	0.897	0.909	0.912	0.879	0.933	0.924	0.913	0.895	0.033	0.893	0.819
Guangdong	0.963	0.964	0.928	0.983	0.794	0.616	0.652	0.693	0.701	0.731	0.803
Beijing	0.810	0.789	0.813	0.787	0.802	0.827	0.794	0.782	0.789	0.782	0.798
Anhui	0.453	0.695	0.623	0.582	0.813	0.904	0.830	0.932	0.913	0.920	0.767
Jiangsu	0.728	0.826	0.782	0.720	0.768	0.913	0.716	0.748	0.719	0.740	0.766
Hunan	0.816	0.900	0.855	0.819	0.844	0.875	0.637	0.679	0.605	0.593	0.762
Fujian	0.889	0.843	0.748	0.806	0.731	0.680	0.661	0.633	0.688	0.678	0.736
Guangxi	0.708	0.809	0.809	0.776	0.789	0.734	0.620	0.602	0.620	0.624	0.709
Liaoning	0.658	0.636	0.814	0.749	0.648	0.655	0.640	0.637	0.615	0.600	0.665
Jilin	0.586	0.687	0.720	0.661	0.634	0.593	0.642	0.584	0.573	0.681	0.636
Inner Mongolia	0.677	0.555	0.610	0.596	0.594	0.565	0.599	0.582	0.550	0.546	0.587
Jiangxi	0.551	0.635	0.625	0.559	0.536	0.509	0.490	0.618	0.678	0.629	0.583
Hubei	0.594	0.728	0.603	0.660	0.599	0.486	0.473	0.572	0.493	0.499	0.571
Shandong	0.623	0.601	0.675	0.586	0.562	0.474	0.521	0.528	0.458	0.499	0.553
Guizhou	0.383	0.490	0.547	0.591	0.577	0.436	0.601	0.715	0.528	0.612	0.548
Sichuan	0.454	0.517	0.516	0.476	0.498	0.363	0.644	0.704	0.557	0.660	0.539
Henan	0.618	0.726	0.701	0.558	0.522	0.490	0.433	0.444	0.453	0.435	0.538
Heilongjiang	0.610	0.574	0.599	0.567	0.566	0.510	0.492	0.481	0.472	0.480	0.535
Ningxia	0.352	0.586	0.613	0.535	0.436	0.444	0.509	0.650	0.554	0.619	0.530
Shanxi	0.559	0.590	0.582	0.503	0.502	0.420	0.436	0.519	0.431	0.433	0.498
Gansu	0.471	0.539	0.621	0.414	0.390	0.382	0.498	0.600	0.529	0.526	0.497
Yunnan	0.416	0.620	0.520	0.394	0.408	0.398	0.463	0.585	0.539	0.593	0.493
Xinjiang	0.321	0.327	0.354	0.490	0.386	0.400	0.535	0.742	0.610	0.689	0.486
Shaanxi	0.430	0.490	0.476	0.475	0.461	0.400	0.505	0.546	0.454	0.455	0.469
Hebei	0.461	0.492	0.459	0.427	0.404	0.381	0.416	0.458	0.405	0.395	0.430
Qinghai	0.314	0.543	0.569	0.506	0.468	0.430	0.471	0.276	0.274	0.253	0.410
Hainan	0.043	0.317	0.200	0.402	0.068	0.066	0.263	0.192	0.326	0.332	0.221

Notes: The table is organized according to the output of MATLAB R2012a.

There are differences in the development trends of the technological innovation efficiencies in each province. For example, the provinces whose efficiency scores show a fluctuant descending tendency are mainly concentrated in eastern and central China, such as Beijing, Fujian, Guangdong, Henan, and Hunan. Western provinces, such as Gansu, Ningxia, Shanxi, Sichuan, and Xinjiang, appear to rise in the relative advantages of efficiency scores. The average efficiency scores of Zhejiang, Tianjin, Chongqing, Shanghai, and Guangdong are all above 0.8, indicating that the technological innovation inputs and outputs in these provinces are more reasonable. Of all the 30 provinces, 26.7% of them are below 0.4 (Hainan, Qinghai, Hebei, Shaanxi, Xinjiang, Yunnan, and Gansu) in terms of efficiency scores, indicating that industrial enterprises in these provinces need to reduce emissions in addition to increasing the innovation inputs.

We select three time points in 2006 (the start time of our datasets), 2010 (the end time of the 11th Five-year plan—for the development of China's economy, the government will formulate a plan every five years, which is the five-year plan—and 2015 (the end time of our datasets) to show the three-dimensional space patterns of efficiency scores, as shown in Figure 2. It can be seen that China's province-level technological innovation efficiencies are characterized by multiple peaks. These peaks are mainly located at 30°–40° north latitude and 120°–140° east longitude, while the largest valley is around located at 35°–45° north latitude and 100°–120° east longitude. These results indicate that the technological innovation efficiency in southeastern China is more efficient. The number and height of peaks have displayed a downward trend over time, indicating that the overall gap in the technological innovation efficiency at provincial level tends to narrow.

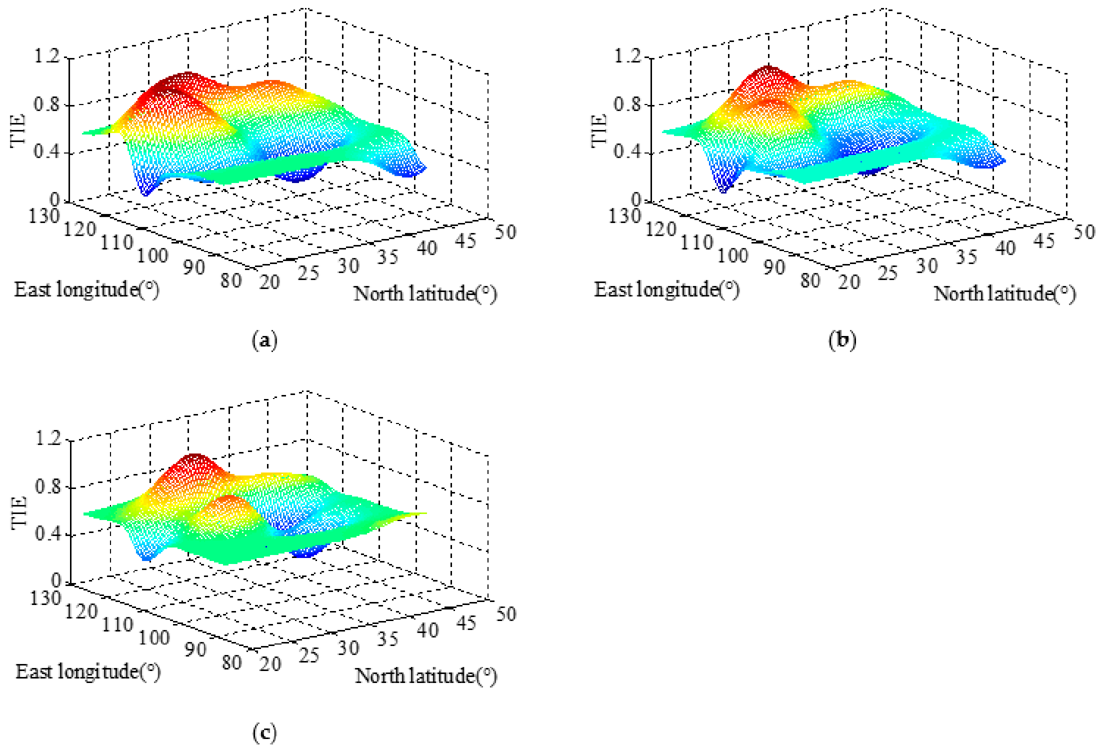


Figure 2. Spatial patterns of technological innovation efficiencies. (**a**–**c**) represent 2006, 2010, and 2015, respectively. The Figures are drawn by MATLAB R2012a.

Overall, the efficiency scores deviate from a uniform distribution, indicating that there may be spatial autocorrelation in China's province-level technological innovation efficiencies. This speculation will be investigated in the next-step test.

4.2. Spatial Autocorrelation Test

The spatial autocorrelation test is used to investigate the global *Moran's I* of China's province-level technological innovation efficiencies in the sample period. According to the approach above, three spatial weights matrices are constructed to determine whether there are adjacent dependencies (M^A), geospatial distance dependencies (M^S), or economic distance dependencies (M^E) in China's provincial technological innovation efficiencies (see Table 2).

As shown in Table 2, China's provincial technological innovation efficiencies of industrial enterprises show a positive spatial autocorrelation. Moreover, there are differences in the development trends of the global *Moran's I* in each spatial weight matrix. For example, in general, the values of M^A and M^E display a fluctuant descending tendency during the period studied, while the value of M^S displays a fluctuant ascending tendency. This result indicates that the adjacent dependence and economic distance dependence of province-level technological innovation efficiencies are weakened during the sample period.

Although there are some spatial autocorrelation findings for China's provincial technological innovation efficiencies, the annual global *Moran's I* can only detect spatial dependence in global regions. It seemingly overlooks the spatial autocorrelation in local regions. Taking the adjacent spatial weight matrix as an example, the *Moran's I* scatter plots for 2006, 2010, and 2015 are drawn to further investigate whether China's province-level technological innovation efficiencies are clustered, as shown in Figure 3.

Table 2. The Global *Moran's I* of technological innovation efficiencies from 2006 to 2015.

Year	2006	2007	2008	2009	2010
M^A	0.270 ***	0.355 ***	0.192 **	0.336 ***	0.328 ***
	(2.665)	(3.337)	(1.977)	(3.158)	(3.193)
M^S	0.143	0.172	0.045	0.208 *	0.274 **
	(1.371)	(1.599)	(0.611)	(1.872)	(2.389)
M^E	0.231 ***	0.264 ***	0.191 **	0.293 ***	0.203 ***
	(3.974)	(2.769)	(2.277)	(3.665)	(3.043)
Year	**2011**	**2012**	**2013**	**2014**	**2015**
M^A	0.339 ***	0.187 *	0.118	−0.021	0.111
	(3.259)	(1.902)	(1.338)	(1.106)	(1.273)
M^S	0.381 ***	0.254 **	0.185 *	−0.125	0.178
	(3.215)	(2.229)	(1.699)	(−0.702)	(1.639)
M^E	0.166 ***	0.358 ***	0.186 ***	−0.132	0.187 ***
	(2.826)	(4.354)	(3.084)	(−1.382)	(3.538)

Notes: z-statistics in parenthesis. *, **, and *** indicate that p values are less than 0.1, 0.05, and 0.01, respectively. The table is organized according to the output of MATLAB R2012a.

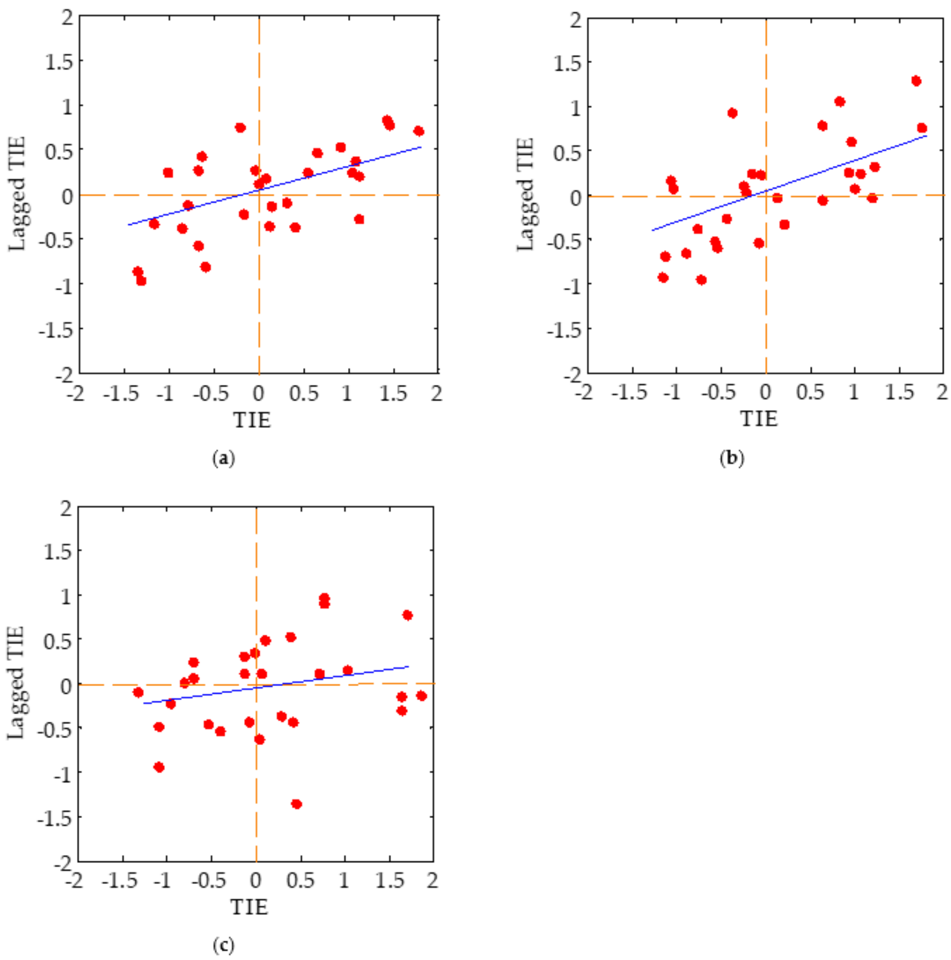
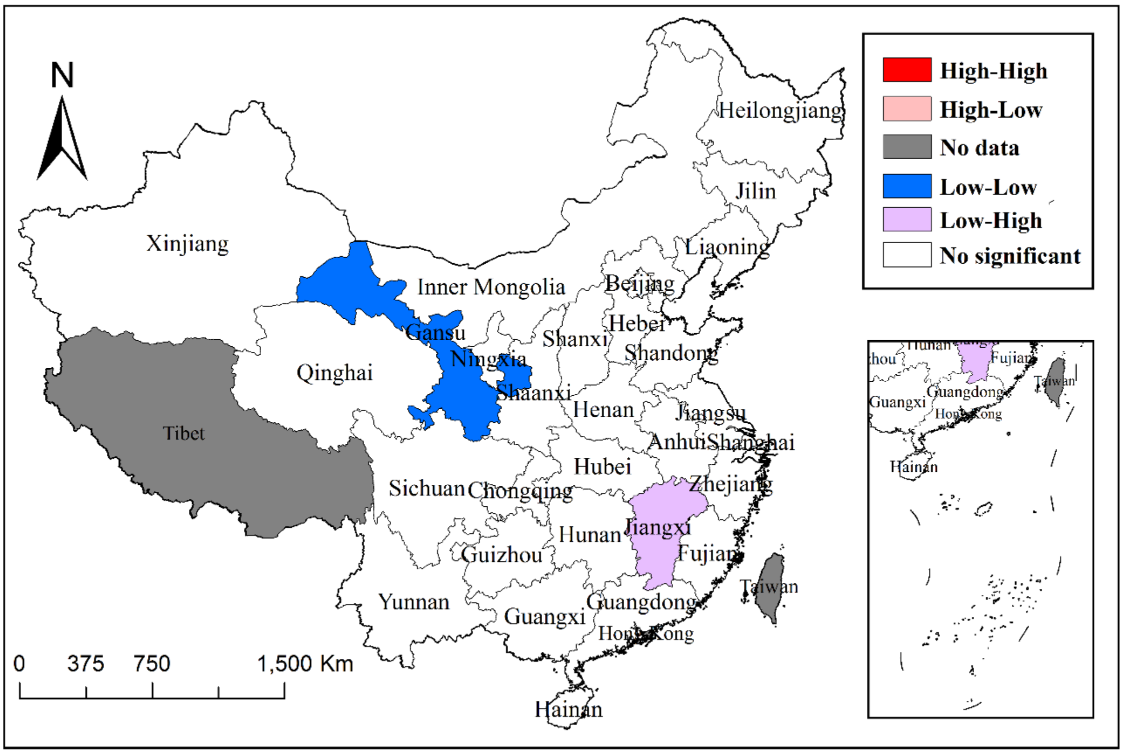
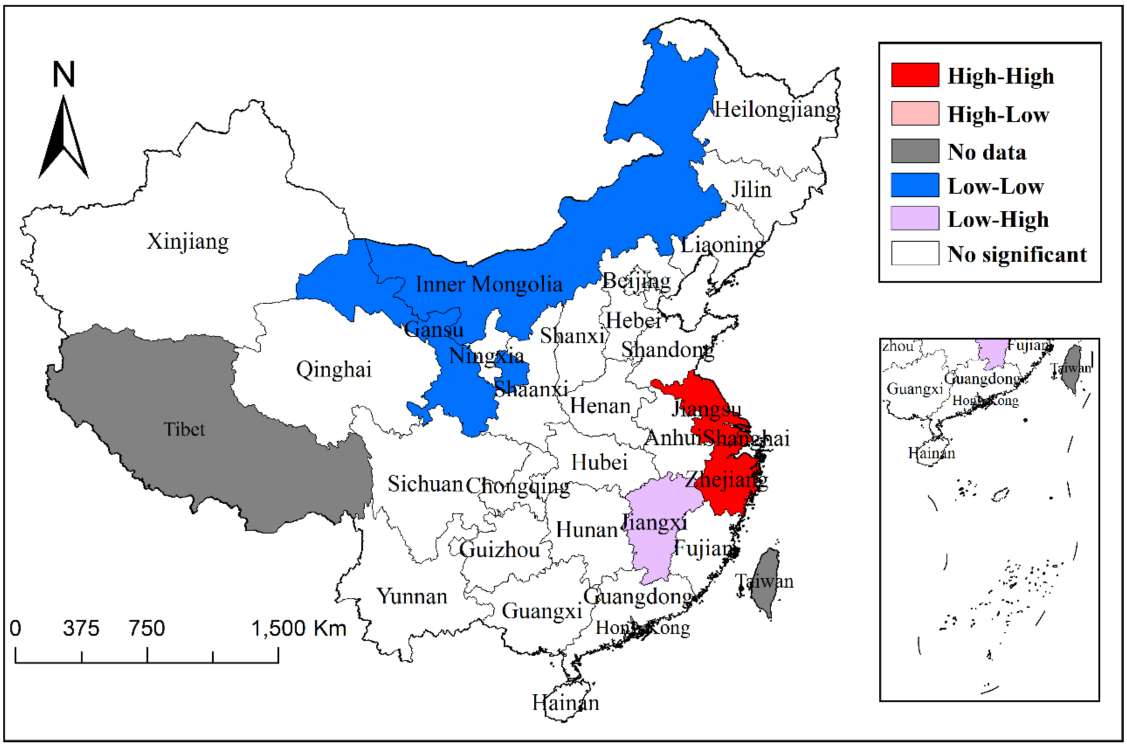


Figure 3. *Moran's I* scatter plots of technological innovation efficiencies. (**a**–**c**) represent 2006, 2010, and 2015, respectively. The Figures are drawn by MATLAB R2012a.

Figure 3 reports that in 2006, 2010, and 2015, 18 sample points (60%), 18 sample points (60%), and 16 sample points (53.3%) are located in the first and third quadrants, indicating that China's province-level technological innovation efficiencies seem to cluster together in space. In addition, corresponding local indicators of spatial association (LISA) also provide visual evidence of spatial clustering for the efficiency of technical innovation in industrial enterprises (see Figure 4).

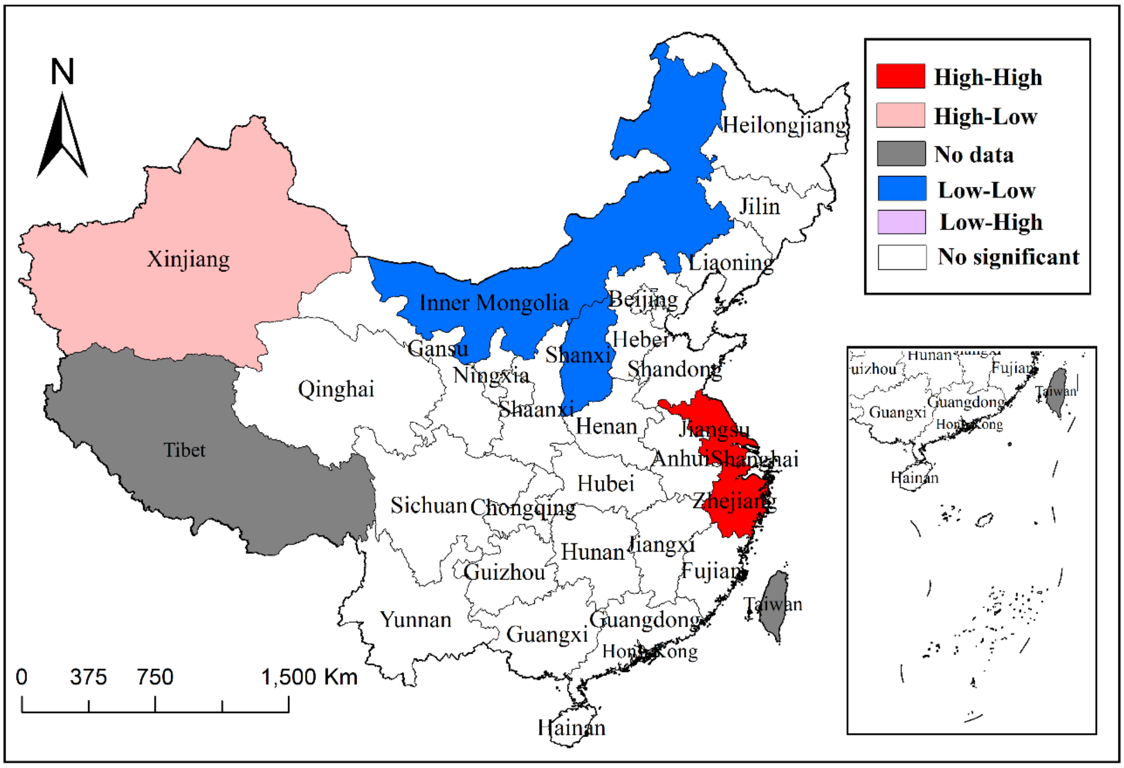


(a)



(b)

Figure 4. *Cont.*



(**c**)

Figure 4. Maps of LISA of technological innovation efficiencies. (**a**–**c**) represent 2006, 2010, and 2015, respectively. The Figures are drawn by ArcGIS 10.3.

As shown in Figure 4, the provinces belonging to the H-H clustering type are mainly concentrated in eastern China, while the provinces belonging to the L-L clustering type are mainly centralized in northwest China. Specifically, in 2006, Gansu (p = 0.01) belonged to the L-L clustering type; Jiangxi (p = 0.05) belonged to the L-H clustering type. In 2010, Inner Mongolia (p = 0.05) joined the L-L clustering type; Jiangsu (p = 0.05), Zhejiang (p = 0.05), and Shanghai (p = 0.05) belonged to the H-H clustering type. In 2015, Jiangsu (p = 0.05) and Zhejiang (p = 0.01) belonged to the H-H clustering type; Xinjiang (p = 0.05) joined the H-L clustering type; Jiangxi (p = 0.05) joined the L-L clustering type. These findings again demonstrate the existence of spatial clustering of China's province-level technological innovation efficiencies.

4.3. Effects of ERs on Technological Innovation Efficiency

4.3.1. The Traditional Panel Econometric Model

For the sake of comparison, a traditional panel model is first constructed, as shown in Table 3. As supplementary analysis, the multicollinearity test for the panel data is conducted. The results of variance-inflating factors (VIFs) show that the multicollinearity among the indicators can be ignored (see Table 3). Before performing econometric analysis, the Hausman test is conducted to determine whether the econometric model is optimal under the fixed effect. According to Table 3, the result of the Hausman test is 25.674 (p = 0.019), implying that the econometric model is more appropriate to use the fixed effect. Moreover, the results of the likelihood ratio (LR) test show that the values of the individual fixed effect and the year fixed effect are significant at the 1% level, indicating that the traditional panel model under the fixed effect is optimal.

Table 3. Results of the traditional panel econometric model.

	OLS	Individual Fixed	Year Fixed	Individual-Year Fixed	VIFs
C	0.604 *** (29.418)				
NOEPA	0.008 (0.169)	0.067 * (1.771)	0.017 (0.355)	0.056 (1.509)	1.72
NOEAPC	0.039 * (1.902)	−0.002 (−0.146)	0.025 (1.267)	−0.004 (−0.302)	1.23
AUOFI	0.093 *** (4.006)	0.025 (1.589)	0.090 *** (3.999)	0.018 (1.207)	1.69
GFS	−0.020 (−1.224)	−0.017 (−1.139)	−0.0001 (−0.020)	−0.011 (−0.687)	2.33
GDP	0.138 *** (2.937)	−0.233 *** (−3.872)	0.140 *** (3.062)	−0.270 *** (−4.433)	4.38
CO_2	−0.210 *** (−3.642)	0.341 ** (3.147)	−0.227 *** (−3.809)	0.479 *** (3.949)	2.05
Log l	90.622	264.977	100.658	283.731	
R^2	0.192	0.118	0.219	0.123	
σ^2	0.033	0.010	0.031	0.009	
Number of observations	300	300	300	300	
LM-lag	38.463 ***	8.738 ***	24.065 ***	0.029	
Robust LM-lag	13.602 ***	0.009	24.824 ***	1.108	
LM-error	27.263 ***	9.144 ***	10.732 ***	0.008	
Robust LM-error	2.516	0.415	11.4904 ***	1.088	
The joint likelihood ratio test (LR)	Fixed effects	Statistics	DOF	p value	
	Individual fixed	366.146	30	0.000	
	Year fixed	37.507	30	0.000	
Hausman			25.674 **		

Note: t-statistics in parenthesis. *, **, and *** indicate that p values are less than 0.1, 0.05, and 0.01, respectively. The table is organized according to the output of MATLAB R2012a. LM denotes the Lagrange multiplier test.

It can be seen that the coefficient of NOEPA is positive but only significant under the individual fixed effect. The coefficient of NOEAPC ranges from −0.004 to 0.039, and none of them pass the significance test except for the OLS model. These results suggest that there is no discernible relationship between regulations and technological innovation efficiency through the traditional panel model. In addition, Table 3 reports that at least one of the LM test is statistically significant in whatever fixed effects incorporated into our model, which indicates that the meta-hypothesis (there is no spatial correlations) does not hold, and the robust LM tests are the same. As a result, when examining the relationship between ERs and technology innovation efficiency at the provincial level in China, the traditional panel model is not enough, and the spatial panel model needs to be considered.

4.3.2. The Spatial Panel Econometric Model

According to LeSage and Pace (2009) research [47], the steps for the spatial panel econometric model are as follows: (1) The panel *Moran's I* needs to be calculated to determine whether the panel data has spatial dependence. (2) The Wald and LR test need to be conducted to determine whether the SPDM model can be transformed to a SPLM model or a SPEM model. It can be seen from Table 4 that the estimation results of the Wald and LR test are statistically significant at the 5% level, indicating that H_0: $\rho = 0$ and H_0: $\delta = -\rho\beta$ are rejected. The SPDM model could not be simplified into the SPLM model or the SPEM model. Therefore, we use the SPDM model to analyze the effects of ERs on the technological innovation efficiency, and the estimation results of the SPLM model and the SPEM model are also listed for reference.

Just focusing on the individual fixed SPDM model (see Table 4), the coefficient of ρ is statistically significant at the 5% level. This result suggests an obvious spatial spillover in the technological innovation efficiency of industrial enterprises. The coefficient of NOEPA is statistically significant at the 5% level, and an increase of 1 in NOEPA will lead to an increase of 0.098 in the technological innovation efficiency. This result indicates that voluntary regulation is positively associated with the efficiency of technological innovation in industrial enterprises. The coefficient of NOEAPC is not statistically significant, indicating that there is no significant correlation between mandatory regulation and technological innovation efficiency.

Table 4. Results of the Spatial Panel Durbin Model.

	SPLM	SPEM	SPDM			
	Individual Fixed	No Fixed	No Fixed	Individual Fixed	Year Fixed	Individual-Year Fixed
intercept		0.600 ***	0.483 ***			
		(24.459)	(7.414)			
NOEPA	0.067 *	0.074 *	0.078 *	0.098 **	0.086 **	0.091 **
	(1.737)	(1.661)	(1.801)	(2.375)	(1.959)	(2.352)
NOEAPC	−0.003	0.038 **	0.028	−0.003	0.012	−0.010
	(−0.218)	(2.172)	(1.487)	(−0.212)	(0.654)	(−0.678)
AUOFI	0.024	0.065 ***	0.051 **	0.014	0.043 *	0.016
	(1.523)	(3.115)	(2.202)	(0.785)	(1.811)	(0.958)
GFS	−0.016	−0.023	−0.041 **	−0.032 *	−0.028	−0.032 *
	(−0.930)	(−1.410)	(−2.326)	(−1.742)	(−1.558)	(−1.808)
GDP	−0.216 ***	0.116 ***	0.157 ***	−0.226 ***	0.159 ***	−0.198 ***
	(−3.607)	(2.554)	(3.269)	(−3.202)	(3.284)	(−2.762)
CO_2	0.371 ***	−0.181 ***	−0.169 ***	0.555 ***	−0.182 ***	0.528 ***
	(3.349)	(−4.154)	(−3.032)	(4.290)	(−3.122)	(4.367)
W * VER			−0.253 *	0.412 **	−0.204	0.260
			(−1.911)	(2.242)	(−1.428)	(1.324)
W * MER			−0.014	−0.002	−0.047	−0.015
			(−0.487)	(−0.110)	(−1.514)	(−0.678)
W * AUOFI			0.058	0.058	0.060	0.063
			(1.110)	(1.466)	(1.064)	(1.579)
W * GFS			0.029	0.052	0.078 **	0.028
			(0.937)	(1.417)	(2.214)	(0.764)
W * GDP			0.025	0.055 **	0.077 **	0.026
			(0.806)	(1.461)	(2.178)	(0.674)
W * CO_2			−0.160	−0.527 **	−0.262	−0.604
			(−1.064)	(−2.087)	(−1.466)	(−1.639)
ρ	0.219 ***		0.374 ***	0.208 **	0.241 ***	−0.023
	(3.010)		(4.910)	(2.409)	(2.877)	(−0.241)
λ		0.471 ***				
		(6.761)				
Log *l*	267.761	105.061	117.820	276.292	127.755	290.659
R^2	0.756	0.170	0.344	0.769	0.377	0.787
σ^2	0.011	0.028	0.026	0.010	0.026	0.008
Number of observations	300	300	300	300	300	300
Wald-lag				15.741 **	31.624 ***	14.067 **
LR-lag				17.124 ***	30.905 ***	13.830 **
Wald-error				14.608 **	39.786 ***	14.050 **
LR-error				16.251 **	39.883 ***	13.851 **
Panel *Moran's I*	0.182 ***					

Note: *t*-statistics in parenthesis. *, **, and *** indicate that *p* values are less than 0.1, 0.05, and 0.01, respectively. The table is organized according to the output of MATLAB R2012a.

As for the control variables, the foreign investment is positively associated with the efficiency of technological innovation in industrial enterprises. The coefficient of GFS is negative and statistically significant, suggesting that the government's financial support might not help industrial enterprises with developing new products in the long term. In addition, the coefficient of spatial lag variable (W * NOEPA) has evident characteristics, indicating that voluntary regulation may have a spatial spillover effect. Therefore, we use the partial differential method to investigate the direct, indirect, and total effects of ERs on the technological innovation efficiency in industrial enterprises, as shown in Table 5.

Table 5. Results of spatial spillovers effect under individual fixed effect.

Variables	Direct	Indirect	Total
NOEPA	0.118 *** (2.635)	0.543 ** (2.257)	0.661 ** (2.510)
NOEAPC	−0.003 (−0.223)	−0.003 (−0.127)	−0.006 (−0.200)
AUOFI	0.015 (0.862)	0.077 (1.555)	0.093 (1.552)
GFS	−0.031 (−1.654)	0.053 (1.144)	0.022 (0.429)
GDP	−0.219 *** (−3.070)	−0.204 (−1.205)	−0.422 ** (−2.354)
CO_2	0.529 *** (4.056)	−0.538 * (−1.840)	−0.010 (−0.035)

Note: *t*-statistics in parenthesis. *, **, and *** indicate that *p* values are less than 0.1, 0.05, and 0.01, respectively. The table is organized according to the output of MATLAB R2012a.

It can be seen that the coefficient of NOEPA shows a statistically significant direct effect, indicating that if a province promulgates voluntary regulation, its technological innovation efficiency will be improved. Furthermore, the indirect effect of NOEPA on the technological innovation efficiency is statistically significant at the 5% level, suggesting that the technological innovation efficiency of one province is affected by the voluntary regulation of neighboring provinces. In contrast, the direct and indirect effects of NOEAPC on the technological innovation efficiency are not statistically significant at the 10% level, which is consistent with our expectations. It can be seen from Table 5 that mandatory regulation has no significant influence on the efficiency of technological innovation in industrial enterprises.

5. Discussion

Strengthening ERs so that they stimulate technological innovation is an academic and practical concern. This study contributes to the grasping of technological innovation efficiency in terms of (1) how the spatial disparity of the efficiency of technological innovation in industrial enterprises and (2) how the relationship between ERs and technological innovation efficiency from a spatial perspective.

As demonstrated empirically, the technological innovation efficiency of industrial enterprises in southeastern China is generally higher than those of provinces in northwestern China. This finding bolsters existing literature that emphasizes the importance of geographic context for technological innovation research [9,12]. This is because industrial enterprises in the southeastern regions usually have relatively rich innovation resources and developed platforms for technology transfer, which induces new product development. Consistent with extensive research on the spatial correlation of similar innovation activities [13,16], our findings demonstrate the existence of spatial dependence in China's province-level technological innovation efficiencies. Some scholars believe that leading industrial enterprises may tend to avoid clusters in the clustering process, because their relative advantages may be impaired [48]. However, our speculation is that provinces with similar technological innovation efficiencies tend to agglomerate within a single cluster in geospatial space, possibly because sub-clustered provinces perform more efficiently through leveraging local knowledge spillovers in relation to new product development [13]. These findings can assist the government in allocating limited fiscal resources more effectively through accurately pinpointing some provinces with high technological innovation efficiency.

The design of ERs plays a key role in promoting the efficiency of technological innovation in industrial enterprises. For example, voluntary regulation can stimulate the technological innovation efficiency of industrial enterprises at the provincial level, possibly because voluntary regulation only specify pollution prevention goals, but provide enterprises with discretion concerning the 'how', which can develop a mutual trust between environmental protection agencies and industrial enterprises [29,31]. In our study, if the government adopts mandatory regulation to restrict industrial enterprises, the enthusiasm of enterprises for technological innovation may be dampened, possibly because mandatory regulation forces enterprises to meet pre-specified environmental standards or else face administrative penalties, then enterprises have to pay for the pollution control technique [6]. These findings extend the Porter's Hypothesis to the case of China's provincial industrial enterprises. Furthermore, our findings provide empirical evidence of the relationship between ERs and technological innovation efficiency, which represents a departure point for future qualitative or quantitative explorations into the Porter's Hypothesis associated with spatial location. These findings can also help the government to promulgate more advanced environmental decision.

The empirical results show that the spatial panel econometric model not only outperforms the traditional panel model but also reveals the spillovers effects of dependent and independent variables. In our case, the efficiency of technological innovation in industrial enterprises has a spatial spillover effect at the provincial level, possibly because the spatial proximity to knowledge can contributes to the exchange of information among provinces improving the efficiency of knowledge transfer [9]. In our study, the technological innovation efficiency of one province is influenced by local voluntary regulation and the neighboring provinces due to the spillovers effect. This is possibly because if a province strengthens ERs, the productive investment of its industrial enterprises is likely to be crowded out, causing some industrial enterprises to transfer to neighboring provinces. In this study, statistical, visual, and spatial methods are combined to test the Porter Hypothesis, which develops a bridge between spatial metrology and the Porter Hypothesis. These findings can also help guide location decisions for industrial enterprises.

The results have several policy implications. First, local governments should capitalize on the agglomeration of innovation activities in industrial enterprises to maximize innovation efficiency. For instance, provinces with high innovation efficiency in southeastern China can increase investment in research funding and experimental equipment to stimulate innovation. Second, local governments should engage in establishing a scientific and effective environmental regulation system. Third, the spillovers effect of innovation activities is also a great way to meliorate technological innovation efficiency. Local governments can establish a cross-provincial innovation demonstration area to encourage knowledge spillovers among provinces. For example, provinces with spatial proximity (i.e., Anhui, Shanghai, Jiangsu and Zhejiang) can set up special funds to guide collaborative innovation.

Author Contributions: Conceptualization: Y.Z. and Z.W.; methodology: Y.Z. and S.Q.; data curation: Y.Z.; writing–original draft preparation: Y.Z., and S.Q.; writing–review and editing: Z.W. and L.Z.

Funding: This work is supported by National Social Science Fund Key Project (18AGL028), Jiangsu Provincial Social Science Fund Series (17ZTB005), Jiangsu Provincial Social Science Key Project (2018SJZDI070), Jiangsu Provincial Social Science Key Project (2018SJZDI064).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Results of descriptive statistics for variable.

Indicators	Variable	Unit	Mean	Max	Min	S.D.
Desirable output	NPIE	10^8 yuan	1586	9127	10	1947
	PAIE	Item	11,195	119,927	37	19,508
Input	PIE	Thousand	78	571	0.00012	105
	EIE	10^8 yuan	67	481	0.181	85
	EIN	10^8 yuan	363	4798	3	572
Undesirable output	ISW	10^4 t	8252	45,576	127	7668
	IWG	100 million cn.m^3	17,288	79,121	860	13,915
	IWW	10^4 t	76,056	296,318	5782	64,153
Explained variable	TIE	%	0.616	0.983	0.033	0.183
Explanatory variables	NOEPA	Item	438	2620	45	267
	NOEAPC	Item	3641	38,434	8	5597
Control variables	AUOFI	10^4 Dollar	4,180,432	80,351,686	1674	6,299,871
	GFS	10^4 yuan	107,768	492,493	70	111,968
	GDP	Billion yuan	15,884	72,812	641	13,665
	CO_2	10^4 t	37,034	136,000	2032	26,182

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