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Influence of Technological Innovation on Regional Green Development Efficiency

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Abstract: Under the background of Green Development, the function direction of technological innovation to green development efficiency, which includes economy, resources and environment, needs to be observed by demonstration. In this paper, the green development efficiency of 30 provinces (cities and districts) in China from 2004 to 2017 is measured and its intertemporal changes, regional differences of green development efficiency are analyzed by using the super efficiency SBM model, further through theoretical analysis and empirical study, the influence of technological innovation on regional green development efficiency and its impact mechanism are investigated. The influence mechanisms of the technological innovation on green development efficiency are clarified and empirically tested by spatial econometric models from the perspectives of the growth sources and quantitative analysis. The results show that during the observation period, the green development efficiency in China exhibits a U-shaped variation, but there are huge regional differences with the obvious polarization in Eastern and Midwestern regions, and that technological innovation has some effect in promoting the region green development efficiency, but not significant enough, which are heterogeneous according to the time periods and regions.

Keywords: Technological Innovation, Green Development Efficiency, Spatial Durbin Model, Meta-US-SBM Model

1. Introduction

Green development is an ecological and economical sustainability concept that lays emphasis on the symbiosis and harmonious development of the economy, society, and environment. Green development efficiency serves as a measure of the input and output efficiency of a country or an area through comprehensive consideration of the resource inputs such as labor, capital, energy, and land as well as the environmental costs. This green framework highlights the degree of coordination among the three aspects of the REE system.

Due to the fact that the rate and orientation of technological reform inflicts an enormous influence upon the environmental effects of social and economic activities, contemporary technologies may possibly lead to or escalate pollution, as well as alleviate or replace existing pollution-causing activities [1]. Khazzom defined the “rebound effect” of technologies as: On one hand, the advancement of production technologies can facilitate energy consumption and cost reduction, curtail environmental pollution and upgrade the level of green development, but on the other hand, this progress can promote the economic growth and increase resource demand, thereby effectuating higher resource consumption, which can produce a considerably adverse impact on green development [2]. The existence of the “rebound effect” necessitates further investigation and empirical studies regarding the impact of technological innovation on the efficacy of green development in terms of economy, resources, and environment.

In recent years, a large number of researchers have actively explored the empirical relationship between technological innovation and the three aspects of green development, and have achieved several significant results. Most empirical studies suggest that technological innovation could promote economic growth and environmental protection, while some papers imply a certain amount of adverse effect on the environment.

Technological innovation tends to influence green development efficiency in two outlooks, namely generality and structure. This deduction implies that the general technological innovation level and structure of technological innovation may exhibit distinct impacts on the orientation and force of green development efficiency. Therefore, this paper explores the means for technological innovation such as regulating green development efficiency through the aspects of generality and structure. This serves the purpose of discovering various mechanisms for technological advancement in order to modify green development efficiency through a framework of the above two aspects. Simultaneously, this paper considers the general effect of technological innovation and the structural effect of innovation input as well as output, with the aim of discovering the orientation that could enhance the efficacy of green development through technological innovation, and also provides policy suggestions for references for the same. The details are shown in Figure 1.

The research idea of this paper includes: Firstly, to elaborate on the dynamics of technological innovation that influence the effectiveness of green development, which is determined in three aspects of the general effect of technological innovation, structure effect of innovation input and output; secondly, employing the Spatial Durbin Model to investigate the spatial externality and heterogeneity of technological innovation impinging on green development efficiency, and enriching and enhancing the existing empirical research knowledge about the influence of technological innovation on green development efficiency; thirdly, applying multiple research methods to obtain mutual verification ensuring the robustness of these empirical results.

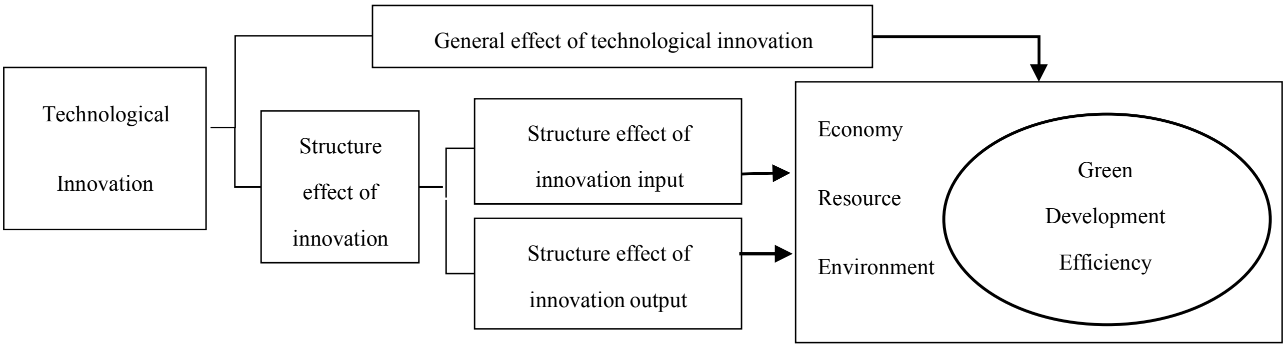

Figure 1. *Methods for Influence of Technological Innovation on Green Development Efficiency.*

2. Measuring Green Development Efficiency

2.1. Green Development Efficiency Measuring Method

Assuming the number of decision-making units (DMUs) is N, then they could be divided into H (H>1) groups as per certain heterogeneous characteristics. The number of DMUs in the h^th group is defined as: $N_h(h=1, 2, \ldots, H)$, $\sum_{h=1}^{H} N_h = N$.

Assuming each DMU possesses three types of input-output variables, represented by the following variables respectively: $x=[x_1, x_2, \ldots, x_M] \in \mathbb{R}_+^M$, $y=[y_1, y_2, \ldots, y_R] \in \mathbb{R}_+^R$, $b=[b_1, b_2, \ldots, b_J] \in \mathbb{R}_+^J$, where, M, R, and J indicate the number of the three types of variables.

Utilizing metafrontier technologies, the production possibility set may be expressed as the following.

$$P^{meta} = \left\{(x,y,b): \sum_{h=1}^{H}\sum_{n=1}^{N_h} \xi_n^h x_n^h \le x^h; \sum_{h=1}^{H}\sum_{n=1}^{N_h} \xi_n^h y_n^h \le y^h; \sum_{h=1}^{H} \xi_n^h b_n^h \le b^h; \xi_n^h \ge 0; n=1,2,\cdots,N_h; h=1,2,\cdots,H\right\} \quad (1)$$

In Formula (1), $P^{\mathrm{meta}} = \{P^1 \cup P^2 \cup \ldots \cup P^H\}$, ξ_n^h Where the weight of the h^th DMU is in the n^th meta-frontier group.

The super-efficiency model is adopted in order to distinguish the DMUs on the frontier and obtain a more robust conclusion. Therefore, this paper employs the Meta-US-SBM (Metafrontier super slack-based mode1 considering undesirable outputs) model to calculate the efficacy of efficient DMUs. At the same time, when the bad output and heterogeneous technologies are taken into account, the non-directional and non-radial SBM efficiency of the o^th decision-making unit ($o = 1,2,\ldots,N_k; k = 1,2,\ldots,H$) in the k^th group with respect to the metafrontier constituted by all groups can be achieved by solving the following program:

$$[Meta-US-SBM]$$

$$\rho_{ko}^{Meta*} = \min \frac{1+\frac{1}{M}\sum_{m=1}^{M}\frac{s_{mko}^{x}}{x_{mko}}}{1-\frac{1}{R+J}\left(\sum_{r=1}^{R}\frac{s_{rko}^{y}}{y_{rko}}+\sum_{j=1}^{J}\frac{s_{jko}^{b}}{b_{jko}}\right)}$$

$$s.t.\ x_{mko} - \sum_{h=1}^{H}\sum_{n=1,n\neq 0\ if\ h=k}^{N_h} \xi_n^h x_{mhn} + s_{mko}^{x} \ge 0$$

$$\sum_{h=1}^{H}\sum_{n=1,n\neq 0\ if\ h=k}^{N_h} \xi_n^h y_{rhn} - y_{rko} + s_{rko}^{y} \ge 0$$

$$b_{jko} - \sum_{h=1}^{H} \sum_{n=1, n\neq 0\ if\ h=k}^{N_h} \xi_n^h b_{jhn} + s_{jko}^b \geq 0$$

$$1 - \frac{1}{R+J}\left(\sum_{r=1}^{R} \frac{s_{rko}^y}{y_{rko}} + \sum_{j=1}^{J} \frac{s_{jko}^b}{b_{jko}}\right) \geq \varepsilon$$

$$\xi_n^h, s^x, s^y, s^b \geq 0$$

$$m = 1,2,\dots,M; r = 1,2,\dots,R; j = 1,2,\dots,J \quad (2)$$

In Formula (2), ε indicates the non-Archimedes infinitesimal. The constraint $1 - \frac{1}{R+J}\left(\sum_{r=1}^{R} \frac{s_{rko}^y}{y_{rko}} + \sum_{j=1}^{J} \frac{s_{jko}^b}{b_{jko}}\right) \geq \varepsilon$ added here guarantees that the denominator of the objective function is not 0. The meaning of other variables remains the same. Similarly, in case of the assumption of variable return to scale (VRS), another constraint $\sum_{h=1,n=1}^{H} \sum_{n\neq 0\ if\ h=k}^{N_h} \xi_n^h = 1$is required.

2.2. Indicator Selection

With reference to relevant literature [3-4] and according to the principles of data availability and integrity, data from 30 provinces (cities and prefectures) of China from 2004–2017 was selected as the sample, excluding Tibet, Macao, Hong Kong, and Taiwan. The observation data was entirely from the *China Environmental Yearbook*, *China Energy Yearbook*, *China Statistical Yearbook*, *China Statistical Yearbook for Regional Economy*, *China City Statistical Yearbook*, and the statistical yearbooks of the provinces (cities and prefectures) over the years.

The selection of input and output variables is as follows:

1) "Good" output (expected output). The actual GDPs computed by the provinces (cities and prefectures) with a constant price in 2000 were selected.

2) "Bad" output (non-expected output). As per the data availability, 6 indicators were selected: CO_2 emission, SO_2 emission, total wastewater discharge, COD emission, ammonia nitrogen discharge in wastewater, and volume of soot (dust) emission. To evade the influence of high relevance and singular value, entropy weight method was adopted to construct the environmental pollution index (EI) and is utilized as the bad output indicator in order to comprehensively reflect the environmental constraint. The value was standardized to 0–100 with a larger value indicating more and a smaller value indicating less pollutant discharge. Unless otherwise stated, the bad output used for the efficiency measurement in this paper is the EI measured through the entropy weight method.

3) Capital input. The 'perpetual inventory method' was adopted to estimate the capital investment. A brief introduction of the method: (1) Selection of current investment indicator. With reference [5], the gross fixed capital formation was selected as the investment of the current year in this study. (2) Measurement of capital stock of base period. With reference [6], Formula (3) was used for the measurement:

$$C_0 = \frac{I_0}{g+\delta} \quad (3)$$

In Formula (3), C_0 indicates the capital stock of the base period, I_0 refers to the gross fixed capital formation of the base period, and 'g' denotes the average growth rate of gross fixed capital formation. Based on the development speed data of gross fixed capital formation provided in China Statistical Yearbook, δ indicates the depreciation rate of each province (city and prefecture) pertaining to the data from Wu [7]. (3) Price conversion. The price index of investment for fixed assets was applied for investment deflation and the relevant data was converted to the prices of the year 2000. Some of the provinces were deficient in the price indexes of investment for fixed assets and these were replaced with the retail price indexes. As a result, the capital input during the t period can be expressed as:

$$C_t = (1-\delta)C_{t-1} + I_t = (1-\delta)^n C_0 + \sum_{i=1}^{t}(1-\delta)^{t-i} I_i \quad (4)$$

4) Labor input. Labor input reveals the population of employees in the provinces (cities and prefectures) over the years.

5) Land input. According to data availability, this study reckoned the construction land areas of each province (city and prefecture) as the land input indicators.

6) Water resource input. The total water consumption was selected as the proxy variable, which covered agricultural, industrial, domestic, and ecological water use information.

7) Energy input. The energy consumption indicators (converted into standard coal) of the provinces and cities were selected.

2.3. Measurement Result of Green Development Efficiency

This paper employs the 'metafrontier super-efficiency SBM model' to measure the dependent variable, i.e., green development efficiency.

Figure 2 showing that: The statistical description of the green development efficiencies for 30 province-level administrative regions around China from 2004 to 2017. From 2004 to 2017, the average green development efficiency level in China diminished initially but increased later on. The efficiency level in 2017 appeared to be higher than the beginning of the observation period (2004) and the level in 2004 seemed to be relatively low. Although China's economic growth experienced a decline, green development efficiency witnessed a general increase, proving that China was by and large switching to green development.

It was noticed that the provinces (cities and prefectures) with higher green development efficiency were mainly located in the eastern coastal areas; while the efficiency levels in the central and western regions appeared to be significantly low, displaying the occurrence of a "polarization" phenomenon. The eastern regions have constantly maintained a relatively higher level of the green development; after dropping to a low position in 2004, the level rose rapidly and greatly exceeded the level of the other regions (the efficiency value equaled twice of that in the central and western regions), and even emerged higher than the level in 2004 as well as the national average level. In addition, the green development efficiency scores of Guangdong, Hainan, Tianjin, and other provinces (cities) were known to be larger than 1 for a longer duration of time. Nevertheless, the efficiency levels of all the other three regions remained well below the national average level. In 2004, the northeast and central regions shared similar efficiency levels, but the central regions exhibited a continuous growth, while the northeast regions demonstrated a decline first, but then improved with a gradual growth rate. The green development efficiency of the western regions has constantly maintained a relatively low level. Thus, the extent of green development of all the regions in China could be ranked from high to low as: eastern, northeast, central, and western regions; and the difference between the western and the other regions has been amplified over the past few years.

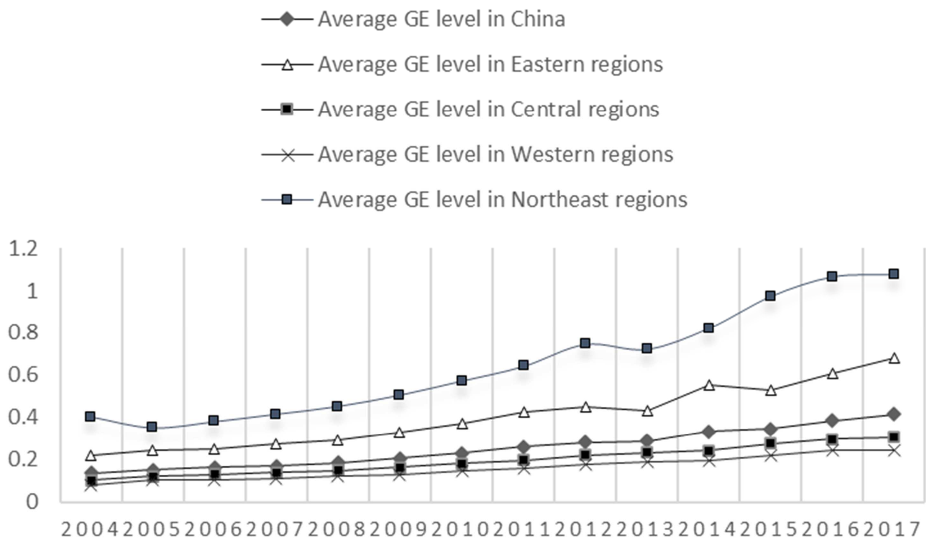

Figure 2. *Statistical Description of the Green Development Efficiency Levels.*

Note: The samples were divided into four regions according to the division method contained in *China Statistical Yearbook for Regional Economy*. The eastern regions included: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Central regions included: Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. Western regions included: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Northeast regions included: Liaoning, Jilin, and Heilongjiang.

3. Measurement Model and Sample Data

3.1. Measurement Model of the Influencing Mechanism for Green Development Efficiency

Along the lines of the objective existence of inter-region economic and social relations, this paper considered the regional spatial association for the study on green development efficiency. For the purpose of observing the spatial association effects of economic phenomena, current studies propose multiple methods, including the most widely applied Moran's I index and Geary's C index.

The calculation method of Moran's I index is shown in Formula (5):

$$I_t = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(Y_{it}-\bar{Y}_t)(Y_{jt}-\bar{Y}_t)}{S^2\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}}$$

$$\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} Y_{\mathrm{it}}\, S^2 = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{\mathrm{it}}-\bar{Y}_t\right)^2 \tag{5}$$

In Formula (5), Y_{it} indicates the observation value of the ith region of the tth period, N the number of spatial entities, i.e. number of provinces (cities and prefectures); w_{ij} indicates the element in the ith row and the jth column of the spatial weight matrix WN. The adjacent matrix form is adopted for the spatial weight matrix WN in this paper, that is, when the two provinces (cities and prefectures) are adjacent geographically, then the w_{ij} value is 1, or the w_{ij} value is 0. Subsequently, the spatial weight matrix WN is subjected to the standardized treatment, i.e. the summary of elements of all rows should equal to 1. Moran's I index represents the coefficient of association between the observation value and the spatial lag value with the value range of [-1, 1]. The Moran's I index value larger than 0 indicates positive autocorrelation, while the value closer to 1 signifies a stronger positive spatial correlation. In case the Moran's I index value is less than 0, it indicates negative autocorrelation. The value closer to -1 denotes stronger negative spatial correlation and the value closer to 0 denotes weaker spatial correlation.

The calculation formula of another common index, Geary's C index is as follows:

$$C_t = \frac{(N-1)\sum_{\mathrm{i}=1}^{N}\sum_{\mathrm{j}=1}^{N} w_{\mathrm{ij}}\left(Y_{\mathrm{it}}-Y_{\mathrm{jt}}\right)^2\left(Y_{\mathrm{jt}}-\bar{Y}_t\right)}{2\left(\sum_{i=1}^{N}\sum_{\mathrm{j}=1}^{N} w_{\mathrm{ij}}\right)\left[\sum_{i=1}^{N}\left(Y_{\mathrm{it}}-\bar{Y}_t\right)^2\right]} \tag{6}$$

In Formula (6), the value of C_t is 0-2 in general. The value larger than 1 indicates negative correlation, smaller than 1 indicates positive correlation and equaling 1 indicates uncorrelated.

Based on the spatial correlation differences between the research samples, the specific forms of spatial measurement models include spatial autoregressive model, spatial error model, and Spatial Durbin Model.

With reference [8, 9], the test steps were implemented to determine the best spatial measurement model in this paper. The detailed steps are as follows:

Step 1. Estimate the following common panel data model without considering spatial effect:

$$Y_{\mathrm{it}} = a + X_{it}\beta + \hbar_t + \mu_i + u_{it} \quad (7)$$

In Formula (7), a indicates the intercept term of the panel model; $\hbar_t$ and μ_i denote the time effect and entity effect, respectively; u_{it} represents the disturbing term changing with the entities and time.

Additionally, Lagrange multiplier (LM) test [10] and the robust LM test [11] were utilized in order to determine whether there is a spatial error effect or lag effect among the samples. If the null hypothesis without spatial effect is rejected in the test, then proceed to Step (2), otherwise proceed to Step (3).

Step 2. Estimate the Spatial Durbin Model of the following panel form:

$$Y_{\mathrm{it}} = a + \rho \sum_{\mathrm{j=1}}^{N} w_{\mathrm{ij}} Y_{\mathrm{jt}} + X_{it}\beta + \sum_{\mathrm{j=1}}^{N} w_{\mathrm{ij}} X_{\mathrm{jt}}\theta + \hbar_t \mu_i + u_{it} \quad (8)$$

In Formula (8), ρ indicates the spatial autoregressive coefficient, which is used to describe the spatial correlation between the green development efficiencies of different regions. The meanings of parameters including w_{ij} have been explained above.

Wald statistics were used to test $H_0^1: \theta = 0$ and $H_0^2: \theta = -\rho\beta$. If both H_0^1 and H_0^2 are rejected, then select Spatial Durbin Model; in case H_0^1 cannot be rejected, then select the spatial autoregressive model; in case H_0^2 cannot be rejected, then select the spatial error model. Besides the above three conditions, the Spatial Durbin Model should be selected with the robustness of results taken into account.

Step 3. Add the spatial lag term of the independent variable in the regression model, in order to verify whether $H_0^1: \theta = 0$. In case H_0^1 cannot be rejected, it indicates that the least square method should be adopted for regression and there is no spatial correlation in any form. Otherwise, $H_0: \rho = 0$ needs to be further tested. In case the hypothesis is rejected, it indicates that the Spatial Durbin Model should be adopted; in case it cannot be rejected, then the spatial lag term WX of the independent variable must be included in the model.

Furthermore, whether to control the entity fixed effect and time fixed effect depends on the Hausman test result and $Corr^2$ value: If the p value of Hausman test result is smaller than 0.025, the control over entity and time fixed effects should be selected; and if the p value of Hausman test result is larger than 0.025, the respective $Corr^2$ values of the random effect model and the fixed effect model should be further observed. In case the $Corr^2$ value of the random effect model appears to be quite large, it would be appropriate to select the random effect model, or the fixed effect model and vice versa.

3.2. Description of Variables and Data

The variables involved in the measurement model consist of:

1) Explained variable: Green development efficiency (GE), expressed with the green development efficiency value measured above.

2) Explaining variable: Technological innovation as the core explaining variable to investigate the impact of technological innovations on green development efficiency.

A. General effect of technological innovation:

The general effect of technological progression reflects the relationship between the overall regional technical merit and green development efficiency. In general, technological innovation activities assist in improving the technical merit of the whole region as well as the industry and permit the application of novel machines, equipment, and methods, facilitating the promotion and popularization of clean energy and environmental protection technologies, improvement of labor productivity and resource and energy utilization efficiencies, as well as the continuous economic growth and reduction of environmental costs. Even so, the perspective of technology-environmental paradox establishes that technology plays a dual role, i.e. technology could bring about various environmental problems, but could also serve as the means to solve them [12]. Although technological development has generated immense material wealth for humankind, it has induced several resource and environmental problems [13]. Along the lines of technological innovation, industrialization led to the extensive progress in productivity and rapid economic development, severe resource exhaustion, industrial pollution, and environmental degradation. To cope with the adverse effect of technology on environmental resources, humanity needs to further develop and administer green technologies and also take remedial actions to protect the natural environment based on technological innovations. It represents the complexity in the relationship between the technical merit and green development efficiency and indicates that it varies with time and place. E.g. at the primary stage of industrialization, the advancement of technical merits was also accompanied by severe environmental pollution and resource consumption problems. Regions at distinct development stages exhibit different relationships between technical merits and green development efficiencies. As a result, the orientation and force of the general effect of technological innovations in practice requires additional comprehensive empirical tests for a substantial determination.

The selection of proxy variables proves pivotal in empirical study. As mentioned above, several studies have quantified total factor productivity as the proxy variable of technological innovations and progress. Nonetheless, total factor productivity is likely to be influenced by many factors including technology, management, system, and infrastructure. Hence, thorough and lucid policy suggestions cannot be deduced based on the research conclusions drawn from total factor productivity as a proxy variable of technological innovation level. Besides, some papers presented the R&D fund investment as a means to reflect the general innovation conditions [14]. However, a huge period of time is consumed for the completion of a technological innovation from the fund investment period to the practical application. Also, the current R&D fund investments contribute minimally to productivity. As high-end achievements of technical development, patents are required to undergo a tedious process of long applications and review prior to the authorization. Related technologies can then be utilized after receiving patent authorization. Thus, once a patent is authorized, it can directly proceed to the promotion phase of economic growth and efficiency improvement [15]. For this reason, the total authorized patents per 10,000 people in terms of invention, utility model, and design are considered as the proxy variable for the general regional technological innovation level.

B. Structure effect of technological innovation

It is noteworthy that the impact of regional technological innovation on green development efficiency under distinct technical structures produces varying results. Technical structure refers to the proportion relation between the various technical methods implemented in technical systems of numerous economic departments in a region within a certain time period. Developed and developing countries retain different technical proportions in their respective technical systems. Combining data availability and focus, this paper considers the input and output structure of several technological innovations, with the former investigating the relative ratio condition of technological innovation input for a variety of innovation subjects in the region and the latter investigating the technical proportion condition with the highest innovation value.

Zhu and Zhang pointed out that the R&D input and patent activity were the most frequently used indicators in current times, employed to weigh the technological innovation input and output condition [16]. Considering the regional technological innovation system, the subjects involved in the technological innovation activities include enterprises, research institutes and universities, individual researchers, etc. As the economic entity pursuing the maximum benefits, enterprises render keen attention to the economic benefits of R&D input in order to gain refined output efficiency. When the R&D input of enterprises accounts for a high percentage in a region, the research undertakings and achievements are more likely to directly and efficiently contribute to the local economy. Likewise, the development of clean production technology level of enterprises would yield a positive effect on the local resource and environmental systems, and further facilitate the enhancement of green development efficiency of the region. According to available data, the R&D staff input proportion of large and medium-sized industrial enterprises is introduced in this paper as a variable, which is expected to bring about a positive impact on green development efficiency. With respect to the structure effect of innovation input, the proportion of the technologies possessing the highest innovation value is critical. The higher the proportion, the more advanced the technical structure of this region, and under such circumstances, it is more likely to promote economic growth and demonstrate minimal resource consumption and environmental pollution. Considering that invention patents possess supreme innovation value and technical content, the high proportion of invention patents would signify the ultimate quality and regional technological innovation level. Therefore, the proportion of invention patents under current authorized patents is used in this paper to present the innovation output structure, while it is anticipated that the refinement of this proportion would improve the green development efficiency level of the region.

3) Control variable: With reference to the relevant investigations of other scholars and selection of the following control variables:

A. Environmental regulation

Numerous domestic and international scholars have delved into the relationship between the environmental regulation and green development efficiency at present [17-19], however, the topic of environmental regulation being an effective promoter of green development efficiency remains a disputed one with no certainty of effectiveness to its merit. As for control variable setting, the significant factor of environmental regulation has been considered in this paper and the proportion of investment on industrial pollution treatment completion in the gross industrial output value was adopted in order to depict the intensity of environmental regulation. However, the influence orientation of environmental regulation on green development efficiency calls for extensive analyses through empirical study.

B. Population size

Population size commands great significance to regional economic and environmental conditions [20-21]. On one hand, the expansion of population size promises sufficient labor resources and fervent demand for commodity and service consumption for local economic growth; on the other hand, it afflicts the local eco-environment with further liability and would most likely generate additional severe environmental pollution complications. Consequently, it becomes arduous to determine whether or not population size expansion would assist in the improvement of green development efficiency from a logical perspective. The total permanent population of each province at the year-end (city and prefecture) was used in this paper to illustrate their population sizes and the spatial measurement method was exercised for undertaking the empirical study on the relationship between the population size and green development efficiency.

C. Energy structure

Diverse energies contribute to varied degrees of environmental problems. China’s coal-based energy structure resulted in massive adverse effects on the eco-environment

[22], hence, it becomes our civic responsibility to include the impact of energy structure on green development efficiency in this study as well. The proportion of coal consumption in total energy consumption was employed in this paper to demonstrate China's energy structure conditions, while its impact on green development efficiency was presumed to be negative.

D. Ownership structure

A few scholars believe that on the one hand, since the operating efficiency of the state-owned enterprises appeared relatively low, the high state-owned enterprise proportion in the region might possibly interfere with the regional resource allocation and impede the growth of regional economic output; on the other hand, state-owned enterprises paid greater attention to environmental pollution, as the enterprises' contribution to environmental pollution would be deemed as the achievements of the management and the environmental costs of the state-owned enterprises were essentially borne by the country [23]. Thus, it transpired to be an uphill task to determine the influence orientation of ownership structure on green development efficiency. For this reason, the proportion of the total industrial output value for state-owned enterprises in the total industrial output value was applied as the proxy variable for ownership structure in this paper for undertaking the empirical investigation analyzing the relationship between ownership structure and green development efficiency.

E. Foreign investment

Numerous scholars have attempted to analyze the relationship between foreign investment and environmental pollution of the host country [24-26]. At present, two hypotheses are making rounds in the academic circle, "Pollution Heaven Hypothesis" and "Pollution Halo Hypothesis". The 'Pollution Heaven Hypothesis' deems that developed countries transferred their pollution intensive industries to the developing countries directed by the foreign investment, and regulated the deterioration of environmental quality of host countries. 'Pollution Halo Hypothesis' presumes that the more advanced and environment-friendly production technologies were brought to the host countries aided by foreign investment, and local enterprises were driven to execute the technical reform through the spillover effect, thus, augmenting the environmental quality of host countries. Under such conditions, it becomes highly impossible to comprehend the actual influence orientation of foreign investment on green development efficiency from a theoretical perspective. The proportion of the industrial sales output for the industrial enterprises with foreign investment and Hong Kong, Macao, and Taiwan investment in that of industrial enterprises above the designated size was utilized in this paper to examine the actual impact of foreign investment on the green development efficiencies for 30 provinces in China excluding Hong Kong, Macao, Taiwan, and Tibet.

F. Industrial structure

The proportion change of non-agricultural output value was applied in several prior investigations using the Clark Law in order to portray the industrial structure upgrade or supererogation process. However, under the influence of information and technological revolution, the major industrialized countries have witnessed a "service-oriented economy" trend and service orientation of economic structure has emerged as one of the most substantial features for industrial structure upgrade. The proportion of the value add of the service sector in GDP was selected in this paper for the empirical investigation of the existence and influence orientation of the industrial proportion increasing effect.

3.3. Data Sources

The data sources for variables are shown in detail in Table 1.

Table 1. *Explanation of Variables.*

Factors	**Proxy variables**	**Abbreviation for Variables**	**Source of data**
Technological innovation	Total authorized patents per 10,000 people	Patent_ per	*China Statistical Yearbook on Science and Technology* *China Statistical Yearbook*
	R&D staff input proportion of large and medium-sized industrial enterprises	S_ indus_ R&D	China Statistical Yearbook on Science and Technology
	Proportion of invention patents under current authorized patents	S_ dis	China Statistical Yearbook on Science and Technology
Industrial structure	Proportion of the value add of the service sector in GDP	S_ser	*China Statistical Yearbook*
Environmental regulation	Proportion of investment on industrial pollution treatment completion in the gross industrial output value	Inves_ output	*China Statistical Yearbook* *China Environmental Yearbook*,
Population size	Total permanent population of each province	Pop	*China Statistical Yearbook*
Energy structure	Proportion of coal consumption in total energy consumption	S_ coal	China Energy Statistical Yearbook
Ownership structure	Proportion of the total industrial output value for state-owned enterprises in the total industrial output value	S_ soe	China Industry Economy Statistical Yearbook
Foreign investment	Proportion of the industrial sales output for the industrial enterprises with foreign investment and Hong Kong, Macao, and Taiwan investment in that of industrial enterprises above the designated size	S_ FDI	*China Statistical Yearbook* China Industry Economy Statistical Yearbook

In order to minimize the influence of heteroscedasticity, the variable data was subjected to the natural logarithmic transformation. It was found that a certain spatial autocorrelation was demonstrated for most independent variables within the observation period after the calculation of Moran's I index and Geary's C index (see Table 2) of each independent variable for each year, inferring that the consideration of the spatial measurement method in this study is vital so as to depict the geographical correlation between samples in a more agreeable manner.

Table 2. *Spatial Autocorrelation of Variables.*

Variables	Moran's I				Geary's C			
	2004	2007	2012	2017	2004	2007	2012	2017
GE	0.143*	0.185**	0.179**	0.203**	0.589**	0.546***	0.506***	0.550***
	[0.090]	[0.036]	[0.035]	[0.015]	[0.009]	[0.005]	[0.002]	[0.001]
Patent_ per	0.226**	0.201**	0.239**	0.306***	0.521***	0.483***	0.523***	0.506***
	[0.016]	[0.031]	[0.010]	[0.002]	[0.006]	[0.004]	[0.003]	[0.001]
S_ indus_ R&D	-0.095	0.007	0.056	0.243**	0.815	0.675*	0.706*	0.537***
	[0.411]	[0.629]	[0.306]	[0.016]	[0.516]	[0.087]	[0.069]	[0.005]
S_ dis	0.322***	0. 092	0. 068	-0.004	0.418***	0.706*	0.495**	0.702
	[0.001]	[0.168]	[0.240]	[0.683]	[0.001]	[0.053]	[0.024]	[0.226]
S_ ser	0.036	0.023	0.117*	0.074	0.503	0.561	0.491*	0.526*
	[0.402]	[0.448]	[0.068]	[0.158]	[0.121]	[0.156]	[0.032]	[0.056]
Inves_output	0.061	0.067	0.312***	0.203***	0.569	0.827	0.753	0.515*
	[0.244]	[0.236]	[0.000]	[0.003]	[0.245]	[0.321]	[0.423]	[0.078]
Pop	0.182**	0.153**	0.171*	0.177*	0.563**	0.601**	0.616**	0.609 **
	[0.036]	[0.042]	[0.045]	[0.043]	[0.011]	[0.015]	[0.023]	[0.021]
S_ coal	0.184*	0.212**	0.285***	0.244***	0.269*	0.532**	0.512***	0.561***
	[0.043]	[0.017]	[0.008]	[0.009]	[0.053]	[0.011]	[0.002]	[0.003]
S_ soe	0.326***	0.348***	0.351***	0.350***	0.567***	0.513***	0.595***	0.562***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.005]	[0.001]	[0.009]	[0.003]
S_ FDI	0.261***	0.301***	0.356***	0.327***	0.502***	0.475***	0.363***	0.356***
	[0.005]	[0.001]	[0.000]	[0.001]	[0.004]	[0.002]	[0.000]	[0.000]

Note: 1. In the square brackets is p value.
2. *, ** and *** stand for at significant level of 10%, 5%, and 1% respectively.

4. Empirical Results and Analysis

4.1. Spatial Effect of Technological Innovation and Green Development Efficiency

The specific impact of technological innovation on green development efficiency is comprehensively analyzed in this paper from the perspectives of spatial direct effect, indirect effect, and total effect, successively. The idea of the empirical study is as follows: Firstly, fit the data of the 30 provinces (cities and prefectures) in China from the year 2004 to 2017. Then, since the global financial crisis originating from the USA in 2008 left a profound and lasting impact on China's economy, the year 2008 was taken as a demarcation point to implement the regression analysis of the conditions of the 30 provinces (cities and prefectures) before and after the financial crisis, i.e. 2004–2007 and 2008–2017. Lastly, the national samples were divided into the eastern and western regions' sub-samples in order to better distinguish between the heterogeneous characteristics of different regions of China.

After the analysis, it was found that the Spatial Durbin Model emerged as the proper model form for the study. The regression results of the spatial direct effect, indirect effect, and total effect for the general effect of technological innovation represented by the number of authorized patents per 10,000 people are reported in Table 3. Further, the detailed analysis is explained.

Table 3. *Regression Results.*

Variables	China (2004-2017)	China (2004-2007)	China (2008-2017)	Eastern regions (2004-2017)	Midwest regions (2004-2017)
Spatial direct effect					
Patent_per	0.073***	0.120***	-0.055*	-0.017	0.109***
	(3.569)	(3.166)	(-1.969)	(-0.468)	(4.370)
S_indus_ R&D	-0.061	0.023	0.087	-0.387***	-0.040
	(-0.890)	(0.250)	(0.853)	(-3.281)	(-0.512)
S_dis	0.165	0.126	0.060	-0.329	0.311*
	(1.156)	(0.661)	(0.344)	(-1.594)	(1.872)
S_ser	1.024***	0.660*	1.451***	3.784***	-0.004
	(4.607)	(1.575)	(4.799)	(8.662)	(-0.014)
Savings_ per	-0.072*	-0.346***	0.151***	0.209*	-0.049
	(-1.685)	(-3.875)	(3.165)	(1.862)	(-1.080)
Inves_output	0.148**	0.172***	0.111	-0.259*	0.175***
	(2.696)	(3.552)	(1.393)	(-2.026)	(3.732)
Pop	-0.055	-0.174	0.007	-0.345	-0.360***

Variables	China (2004-2017)	China (2004-2007)	China (2008-2017)	Eastern regions (2004-2017)	Midwest regions (2004-2017)
	(-0.934)	(-0.548)	(0. 101)	(-1.626)	(-5.429)
S_coal	-0.656***	-0.405	-0.550***	-0. 675**	-0.463***
	(-4.0175)	(-1.544)	(-2.822)	(-2.587)	(-3.248)
S_soe	0.096	0.203	0.137	0.387	-0.145
	(1.088)	(1.444)	(0.866)	(1.374)	(-1.479)
S_FDI	0.270*	0.181	-0.172	0.674**	0.602**
	(1.920)	(0.742)	(-0.717)	(2.903)	(2.524)
Spatial indirect effect					
Patent_per	0.001	0.106	0.023	-0. 224**	-0. 137**
	(0.012)	(0. 161)	(0. 285)	(-2.716)	(-2.773)
S_indus_ R&D	0.437***	0.343*	0.203	-0.094	0.027
	(2.665)	(1.568)	(1.013)	(-0.518)	(0.210)
S_dis	-0.269	0.605	1.532**	-0.686*	-0.252
	(-0.902)	(1.061)	(2.347)	(-1.762)	(-0.877)
S_ser	1.202**	0.470	2.104**	2.704*	-0.337
	(2.052)	(0.421)	(2.036)	(2.027)	(-0.154)
Savings_ per	-0.042	0.156	-0.194	0.821***	-0.004
	(-0.351)	(0.521)	(-1.070)	(3.272)	(-0.031)
Inves_output	0.107	-0.055	0.080	-0.182	-0.072
	(0.594)	(-0.296)	(0.258)	(-0.564)	(-0.627)
Pop	-0.207*	-0.477	0.033	-1.545**	0.104
	(-1.577)	(-0.747)	(0.139)	(-0.832)	(1.044)
S_coal	-1.019***	-1.214*	-1.483***	-0.239	0.007
	(-2.780)	(-1.655)	(-2.723)	(-0.381)	(0.050)
S_soe	-0.397**	-0.224	-0.369	-0.523	-0.630**
	(-2.095)	(-0.529)	(-0.857)	(-1.076)	(-2.740)
S_FDI	1. 283***	1. 234*	1. 077	1. 329**	1.367***
	(2. 966)	(1.814)	(1.671)	(2. 226)	(3. 271)
Spatial total effect					
Patent_per	0.072	0.137	-0.034	-0.220*	-0.023
	(1.349)	(1.464)	(-0.323)	(-2.060)	(-0.618)
S_indus_ R&D	0.352**	0.368	0.281	-0.475	-0.004
	(2.055)	(1.434)	(1.180)	(-1.591)	(-0.018)
S_dis	-0.084	0.683	1.518**	-1.068**	-0.052
	(-0.411)	(1.062)	(2.211)	(-2.108)	(-0.013)
S_ser	2.164***	1.287	3.424***	6.118***	-0.347
	(3.045)	(1.001)	(3.009)	(3.837)	(-0.721)
Savings_ per	-0.118	-0.223	-0.034	1.015***	-0.056
	(-0.875)	(-0.763)	(-0. l90)	(3. 471)	(-0.462)
Inves_output	0.255	0.118	0.191	-0.434	0.104
	(1.251)	(0.631)	(0.533)	(1.115)	(0.765)
Pop	-0.291*	-0.596	0.038	-2.009**	-0.159**
	(-1.835)	(-0.852)	(0.196)	(-2.669)	(-2.067)
S_coal	-1.487***	-1.466*	-2.097***	-0.875	-0.499*
	(-4.072)	(-1.871)	(-3.082)	(-1.162)	(-1.605)
S_soe	-0.330	-0.004	-0.267	-0.174	-0.715***
	(1.418)	(0.008)	(0.527)	(0.203)	(3.054)
S_FDI	1.423***	1.285*	0.811	1.839**	1.736***
	(2.870)	(1.572)	(1.092)	(2.423)	(3.706)
Wald Spatial Lag test	61.680***	25.971***	34.604***	161.870***	38.613***
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]
Wald Spatial Error Test	63.287***	22.206***	44.864***	166.165***	40.668***
	[0.000]	[0.004]	[0.000]	[0.000]	[0.000]
Log Likelihood	302.382	260.760	189.530	198.774	243.038
$Corr^2$	0.473	0.353	0.479	0.722	0.373
Hausman Test	11.126	90.305***	23.086	5.193	12.667
	[0.836]	[0.000]	[0.198]	[0.900]	[0.779]
Entity fixed effects	Uncontrol	Control	Uncontrol	Control	Uncontrol
Time fixed effects	Uncontrol	Control	Uncontrol	Control	Uncontrol
Obs	420	120	300	154	266
R^2	0.846	0.922	0.945	0.932	0.875

Note: 1. In the square brackets is p value.

2. *, ** and *** stand for at significant level of 10%, 5%, and 1% respectively.

3. The fixed effect model is used in the second column on the left since the Hausman test is insignificant and the $Corr^2$ value of the fixed effect model is larger.

Generally at the national level from 2004 to 2017: The overall technological innovation level significantly endorses the enhancement of green development efficiency level at 1% level, but its positive influence remains quite weak, that is, for each 1% growth of the number of patents per 10,000 people, green development efficiency increases by only 0.07% and its spatial control impact on green development efficiency appears insignificant; the impact of the structure of innovation input on green development efficiency also seems insignificant, but its indirect impact on the efficacy is significantly positive at 1% level; both the direct and indirect impacts of innovation output structure on green development efficiency come across as insignificant.

Compared to the regression results of the national samples before and after 2008, it is quite evident that: With the premise of other conditions remaining unchanged, with each 1% growth of the total number of authorized patents per 10,000 people before 2008, the green development efficiency level increases by 0.12%, but after 2008, contrarily, each 1% growth prompts a drop of 0.055% in the efficiency level. The data propose that the statement reporting that ‘overall technological innovation level promotes green development efficiency’ remains valid only prior to 2008 and the influence orientation changes from positive to negative after 2008. It is further established that there exists clear temporal heterogeneity for general effect of technological innovation. In terms of the structure effect of innovation, the direct impact of the input and output structures of technological innovation on green development efficiency seem insignificant before and after 2008. The spatial spillover effect of the input structure of innovation on green development efficiency before 2008 is significantly positive, and remains positive until after 2008 when it becomes insignificant. The indirect impact of the output structure of innovation on green development efficiency is insignificant before 2008 and its impact on green development efficiency effectuates a significantly positive spatial spillover effect after 2008, portraying the outstanding temporal heterogeneity of the structure effect of innovation.

In the regional regression results, the direct impact of the number of authorized patents per 10,000 people in the eastern regions on green development efficiency seems insignificant, exhibiting the insignificant general effect of technological innovation. However, its indirect impact on green development efficiency appears significantly negative, that is, with each 1% growth of the number of authorized patents per 10,000 people in the eastern regions, the green development efficiency for the surrounding areas of the province decreases by 0.225%. The impact of the general effect of technological innovation on green development efficiency remains significantly positive in the central and western regions and the contribution level stays higher than the national average level. Nonetheless, the indirect impact of the general effect of technological innovation on green development efficiency in the central and western regions is significantly negative, and the spatial negative influence degree stays at a lower level than that in the eastern regions. In terms of the general effect, the growth of the number of authorized patents per 10,000 people in the eastern regions is significantly and negatively correlated with green development efficiency, and the negative correlation is analogous to the central and western regions but remains insignificant. It suggests that there exists a certain regional heterogeneity for the general effect of technological innovation, that is, the negative effect degree of the technological environment for the eastern regions appears higher than that of the central and western regions. As for the structure effect of innovation, the direct impact of the structure effect of innovation input for the eastern regions on green development efficiency seems significantly negative with an insignificant indirect impact, however, both these impacts are insignificant with respect to the central and western regions. Inside the eastern regions, the direct impact of innovation output structure effect on green development efficiency is insignificant and the impact on the surrounding provinces and cities generates a significantly negative spillover effect. Though no significant spatial spillover effect occurred in the central and western regions, the direct impact of the innovation output structure effect on green development efficiency is significantly positive, revealing a certain spatial heterogeneity for the structure effect of technological innovation. The heterogeneity in the eastern regions is mainly presented through the negative influence on green development efficiency. As a result, the effect of enhancing green development efficiency level through the structure effect of technological innovation appears significantly valuable in the central and western regions.

4.2. Robustness Test

To examine the robustness of regression results, the same measurement method was applied to study the three mechanisms, namely the generality of technological innovation, structure of technological innovation, and innovation output structure, successively and independent of each other. The results illustrated that there was no apparent difference between the critical coefficient marking and the significance conditions during separate regression and the relevant regression coefficient conditions, with the consideration of the three mechanisms, confirming the high reliability of the regression results reported in Table 3.

5. Conclusions

All the above empirical results suggest that, on a national scale, the general effect of technological innovation presents a weak positive impact on green development efficiency, and the direct impacts of the structure effects of innovation input as well as output produce insignificant effects on green development efficiency. The overall effect of technological innovation in promoting green development efficiency was valid only before 2008 and the influence orientation turned from positive to negative post 2008. The structure effects of both technological innovation input and output, before and after 2008, possess no direct significant influence on green development efficiency. Technological innovation indeed promotes regional green development efficiency, but the promotional effect is not significant. It is discovered through measurement and tests that enterprises with the most powerful technological innovation drive and invention patents with supreme innovation value, are not essentially critical in promoting regional green development efficiency, and instead produce a drop in the efficiency to some degree. In this paper, it is presumed that the "economic growth driver" with the essence of technological innovation may be the key component of this phenomenon. Technological innovation has been constantly deemed as one of the significant drivers for economic growth, and the focus of technological innovation during the history of human society remained on the methods that effectuate the productivity and production efficiency. At the beginning stage of industrialization, the positive effect of output growth arising from technological innovation was substantially higher than the negative effect on the eco-environment due to the development of productivity. The significantly positive general effect of technological innovation on green development efficiency in the central and western regions from 2004 to 2017 ascertains this viewpoint as well. With the expansion of industrialization, there is greater economic growth but there is a sharp increase in pollutant discharge, leading to severe impairment of the environment. The rate of increase for the negative environment effect due to technological innovation gradually exceeds the positive economic effect, presenting issues such as a more prominent negative influence of resource consumption and environmental pollution. Thus, a more pragmatic approach is required to address this issue of utilizing technological innovation in an effective manner in order to be productive as well as resolve the environmental problems.

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