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Research Article

Spatial Econometric Study on the Impact of Industrial Upgrading on Green Total Factor Productivity

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Under the background of high-quality development led by the new development concept in China, it is imperative to change the development mode, optimize the economic structure, and transform the driving force, and industrial upgrading is the necessary way to promote the optimization of the industrial structure and achieve high-quality economic development. Based on data covering 284 prefecture-level cities in China, this paper first calculates the green total factor productivity (GTFP) of each prefecture-level city and then constructs three spatial econometric models (SLM, SEM, and SDM) based on four spatial weight matrices to empirically analyze the impact of industrial upgrading on GTFP. The results show that the GTFP of all cities in China shows a fluctuating upward trend and significant spatial spillover effect. Both full-sample and regional heterogeneity tests show that industrial upgrading can promote growth in GTFP, but the promoting effect on different regions is different. Regarding the control variables, GTFP has an inverted U-shaped relationship with economic development; additionally, human capital and financial development play a driving role in GTFP, while population density plays a restraining role. Finally, based on the empirical findings, we propose a multipronged policy of differentiated industrial policy and a variety of complementary measures to promote GTFP growth.

1. Introduction

Since the beginning of the reform and opening up, China has created a miracle of growth, with an average economic growth rate of 9.8% for 34 consecutive years. However, the environmental pollution, resource waste, and overcapacity behind this growth which have been revealed are becoming increasingly serious. Therefore, under the background of increasingly tight resource and environmental constraints, how to realize the coordinated progress of high-quality development and environmental protection has become an important problem in China's development which remains to be solved.

Rapid economic development is usually accompanied by large-scale and continuous industrial restructuring and upgrading, which usually evolve in the order of the primary industry, the secondary industry, and the tertiary industry. The key to industrial upgrading is the transfer of resources from sectors with low production efficiency to those with higher production efficiency to continuously improve the efficiency of resource allocation in the economy, which is concentrated in the increase in total factor productivity (TFP), namely, the so-called "structural dividend." Under resource and environmental constraints, GTFP includes natural resource input and environmental pollution in the calculation, which helps to evaluate economic development performance more accurately and comprehensively. Therefore, how to achieve coordinated economic development and environmental protection in the new era, promote the coordinated development of the industrial structure into a green industry system, and become a new driving force to promote high-quality economic growth is an important problem in China's development that must be solved.

To that end, after considering spatial and environmental factors, this paper incorporates industrial upgrading and GTFP into the same analytical framework, uses panel data covering 284 prefecture-level cities to construct a spatial econometric model, analyzes the promoting effect of industrial upgrading on GTFP in different regions through heterogeneity tests, and proposes corresponding policy recommendations based on the empirical results. The structure of this paper is as follows: the first part is the introduction, the second part is the literature review, the third part is the mechanism analysis, the fourth part is the research design, the fifth part is the empirical result analysis, and the sixth part is the conclusion and policy suggestions.

2. Literature Review

2.1. Research on the Impact of Industrial Upgrading on TFP. Berthélemy and Söderling [1] studied 27 African countries and found that adjustment of the industrial structure stimulates a rise in TFP and local economic development. Conducting a statistical analysis of industries in Taiwan, Chang and Oxley [2] discovered that industrial agglomeration and geographical innovation can produce an obvious rise in total factor energy productivity. Based on a study of the impact of economic development transformation on productivity in BRICS countries, Devries et al. [3] also found that adjustment of the industrial structure is the major driving force of the increase in TFP in China. In the case of Vietnam, Huang [4] drew the same conclusion. Wei et al. [5] discovered that the impact of industrial agglomeration on TFP has a threshold, which means that excessive agglomeration curbs productivity, and the agglomeration effect turns into the crowding effect. Based on 1973–1990 panel data covering 39 countries, Fagerberg [6] drew the conclusion that the transformation of the industrial structure is unfavorable for increasing manufacturing productivity.

2.2. Research on the Impact of Industrial Upgrading on GTFP. In contrast, Yuan et al. [7] concluded that the agglomeration of manufacturing industries can improve green economic productivity through the mediating effects of industrial structure upgrading. Song et al. [8] discovered that structural upgrading in the economic development belt along the Yangtze River fails to boost GTFP and that the current industrial structure is not effective in improving ecological productivity or regional economic development. Tao et al. [9] calculated and analyzed the GTFP in 270 prefecture-level cities in China and found that GTFP has obvious spatial spillover effects and is impeded by the transformation of the industrial structure. Based on 1994–2014 panel data covering 30 provinces in China, Feng et al. [10] concluded that GTFP has replaced industrial structure green adjustment (ISGA) as the main driving force of economic development in the provinces and that GTFP plays a key role in the "structural dividend" unleashed by ISGA. Based on the spatial lag model (SLM), Zhao et al. [11] studied the correlation between industrial structure distortion and urban ecological efficiency. They found that industrial structure improvement can remarkably increase ecological efficiency but may also be restrained by natural resources and that optimization of the industrial structure is not obviously effective in affecting ecological efficiency. Long et al. [12] investigated the spatial and temporal distribution and the influencing factors of China's industrial emissions. They found that industrial emissions are characterized by notable agglomeration effects and spatial autocorrelation and that the structure of the industrial scale exerts a positive influence on the productivity of industrial carbon. Xia and Xu [13] recalculated and analyzed the GTFP in all provinces of China with a nonparametric method and discovered that GDP, total factor productivity (TFP), and GTFP display obvious differences in terms of the time trend change, that the efficiency of economic growth suffers a larger loss when environmental factors are taken into consideration, and that industrial structure upgrading, including an increase in the service sector and a decrease in the secondary industry, makes significant contributions to the increase in GTFP [14].

2.3. Research on Other Influencing Factors of GTFP. Using the BML index, Wang et al. [15] calculated the change in GTFP in industry sectors between 2005 and 2015. Their results show that China's GTFP is on the rise overall, and their panel quantile regression results reveal that optimizing the energy structure and promoting technological progress can obviously increase GTFP. Chen et al. [16] also calculated the change in GTFP in China's 36 industrial sectors between 2000 and 2004 by using the GML productivity index, and they found that China's GTFP is continuously on the rise. The research divides the industrial structure into EN, CA, PR, and ES, uses a dynamic panel data model to analyze the impact of the industrial structure on GTFP, and finds that CA exerts a negative influence on GTFP, while EN, PR, and ES exert a positive influence. Cui et al. [17] also found that the structure of resource investment and the energy structure can lead to an obvious increase in GTFP, while technological innovation cannot do so. In contrast, Liu et al. [18] concluded that the constant increase in GTFP in 30 provinces between 1998 and 2013 is mainly driven by technological progress and that GTFP varies with different regions. The effects of GTFP are more obvious in eastern and central provinces than in western provinces. Wang and Feng [19] studied 163 countries (or regions) and found that the technology gap between regions is the main factor affecting GTFP. Zhang [20] made a similar discovery. Li and Lin [21] studied the impact of industrial structure upgrading on green productivity and found that the deepening of capital in the industrial structure represses TFEE and TFCE, while the labor flow in the industrial structure can promote TFEE and TFCE. Liu et al. [22] discovered that technological progress and labor savings are the driving force of GTFP. Liu and Feng [23] showed that technological advances in agricultural output, energy use, and pollutant disposal are growth factors that promote green total factor productivity in agriculture, while technological regression in capital use is a major obstacle to growth.

In summary, most of the literature has established traditional panel models, ignoring the spatial interaction between variables. The research scope is mainly based on provincial panel data. A few studies use spatial econometric models and prefecture-level data.

Therefore, this paper takes prefecture-level cities as the research object, calculates the GTFP and industrial structure upgrading index, and analyzes the dynamic and spatial effects of industrial upgrading on GTFP. Compared with the literature, this paper uses 2006–2019 data covering 284 cities, which makes the research results more responsive to reality. At the same time, the GML index and SBM are used to measure GTFP, which makes the empirical conclusions more reliable.

3. Mechanism Analysis

Industrial upgrading includes two parts: factor input growth and utilization efficiency improvement. GTFP includes the joint effect of environmental regulation, technological progress, resource allocation, scale efficiency, and other factors on output in addition to factor input. Green total factor productivity actually reflects the comprehensive use efficiency of production factors. Industrial structure upgrading is the pursuit of not only growth in advanced industrial production investment but also improvement in industrial economic efficiency and technological progress under the consideration of environmental factors.

For industry as a whole, improvement in production technology and adjustment of the industrial distribution can be summarized based on two aspects: rationalization and advanced industrial structure. The former refers to the flow and allocation of production factors and resources among different industrial sectors, while the latter refers to the redistribution of production resources to higher-grade industries and the upgrading of socially leading industries. Since GTFP emphasizes the coordinated development of economic growth and the ecological environment, it requires that the allocation of resource elements should be adjusted from a relatively unreasonable to a relatively reasonable direction to promote economic growth. It also needs to adjust and shift to environmentally friendly industries to reduce the environmental pressure in the process of economic growth.

The direct role of industrial upgrading in promoting green total factor productivity is mainly reflected in the three following aspects: (1) In the process of upgrading the industrial structure, the development of emerging industries can gradually replace the secondary industry as the leading industry in economic development, improve the overall industrial technical efficiency of a region, and reduce resource consumption and pollution emissions. (2) One of the most important manifestations of industrial upgrading is the coordinated division of labor among industries. That is, the rationalization of industry and the enhancement of the professional division of labor reduce transaction costs, improve production efficiency and scale efficiency, optimize the allocation of resource elements among industries, and promote the growth of the regional green economy. (3) Industrial upgrading forms an industrial structure dominated by the service industry, which makes the living service industry with low productivity gradually shift to a productive service industry with high added value. The refinement of the internal structure of the industry can optimize the allocation of resource elements, further optimize the energy structure, reduce vicious competition, achieve an increase in industrial economic and environmental benefits, and promote a rise in GTFP.

4. Research Design

4.1. Empirical Model. Considering the agglomeration effect and spatial spillover effect of green total factor productivity, this paper uses a spatial econometric model to analyze the relationship between them. The corresponding formulas of the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) are as follows:

$$\begin{aligned} &Y = \rho WY + \beta X + \varepsilon,\\ &Y = \beta X + \varepsilon,\\ &\varepsilon = \lambda \mathrm{W}_{\varepsilon} + \mu,\\ &Y = \rho WY + \beta X_i + \theta W X_i + \varepsilon, \end{aligned} \tag{1}$$

where X and Y are the independent and dependent variables, respectively, X_i are the independent variables, X_j are the control variables, ρ are the spatial regression coefficients, W are the spatial weight matrices, λ are the spatial error coefficients, θ are the spatial regression coefficients of the explanatory variables, and ε, μ are the random perturbation terms.

To investigate the impact of industrial upgrading on GTFP, this paper constructs the SLM, SEM, and SDM. The formulas are as follows:

$$\begin{aligned} &\mathrm{GTFP}_{\mathrm{it}} = \rho_1 w_{ij} \mathrm{IS}_{\mathrm{it}} + \sum_i \beta_i X_{\mathrm{it}} + \varepsilon_{\mathrm{it}},\\ &\mathrm{GTFP}_{\mathrm{it}} = \beta_1 \mathrm{IS}_{\mathrm{it}} + \sum_i \beta_i X_{\mathrm{it}} + \lambda w_{ij} \varepsilon_{\mathrm{it}} + \mu_{\mathrm{it}},\\ &\mathrm{GTFP}_{\mathrm{it}} = \rho_1 w_{ij} \mathrm{IS}_{\mathrm{it}} + \sum_i \beta_i w_{ij} X_{\mathrm{it}} + \varepsilon_{\mathrm{it}}, \end{aligned} \tag{2}$$

where GTFP is green total factor productivity, i and t are the cross-sectional and time dimensions, respectively, IS is the upgrading of the industrial structure, X represents the respective control variables, and β_i is the coefficient of the control variables. The spatial weight matrices selected in this paper include the adjacent weight matrix ($W1$), the inverse distance weight matrix ($W2$), the economic weight matrix ($W3$), and the economic geographic nesting matrix ($W4$).

4.2. Variable Selection

4.2.1. Explanatory Variable: Green Total Factor Productivity (GTFP). In this paper, the dynamics of GTFP in 284 cities in China between 2006 and 2019 are measured using the Malmquist-Luenberger index based on nonradial SBM directional distances, with reference to the set of probabilities constructed by Färe et al. [24], which includes both desired and undesired outputs. GTFP covers labor, capital, and energy input profiles, taking into account both increases in expected output and decreases in expected output. The Malmquist-Luenberger index formula in this paper is shown below:

$$ML(x_{t+1}, y_{t+1}; x_t, y_t, b_t) = \sqrt{\frac{E^t(x^{t+1}, y^{t+1}, b^{t+1})}{E^t(x^t, y^t, b^t)} \frac{E^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{t+1}(x^t, y^t, b^t)}}, \quad (3)$$

where ML is green total factor productivity and x, y, b represent indicators of input, desired output, and undesired output, respectively. The input indicators include (1) labor input, which is expressed in terms of the number of people employed in each city; (2) capital input, which is expressed in terms of the level of the capital stock in a city; and (3) energy consumption, which is expressed in terms of the annual city-wide electricity consumption in each city. The output indicators include (1) desired output, which is expressed in terms of a city's GDP (additionally, the price index is used to eliminate the influence of the price factor, using the year 2000 as the base period), and (2) undesired output, which includes emissions of wastewater, SO_2, and dust. We use the entropy value method to determine the weight of undesired output and to calculate a composite indicator of undesired output.

This paper uses MaxDEA to calculate the Malmquist-Luenberger index of GTFP at constant returns to scale. This index is broken down into technical efficiency change (EC) and technological progress efficiency change (TC). If EC is greater than 1, it indicates that technical efficiency has been improved; in contrast, if it is less than 1, it means that technical efficiency has decreased. If TC is greater than 1, it indicates that technological progress has occurred; otherwise, it means that there has been technological retrogression. Table 1 and Figure 1 show the average value of the ML index of GTFP and its decomposition terms for 284 prefecture-level cities from 2006 to 2019. Overall, the growth rates of GTFP and TC show a fluctuating upward trend, while EC shows a fluctuating downward trend.

Table 1: Average values of the ML index and its decomposition terms from 2006 to 2019.

Year	ML	EC	TC	IS
2006	0.91916	1.05197	0.87682	0.25578
2007	0.93405	0.98597	0.95316	0.2528
2008	0.9424	1.03035	0.91496	0.26218
2009	0.94324	1.0043	0.93862	0.26828
2010	0.95732	1.00919	0.94771	0.26375
2011	0.95384	0.97026	0.98423	0.26962
2012	0.96249	0.98363	0.97954	0.26841
2013	0.91206	1.09318	0.83482	0.28684
2014	0.99069	1.463	0.67765	0.27769
2015	1.00051	1.22027	0.82232	0.29406
2016	1.0066	1.05083	0.95827	0.27672
2017	0.99973	1.2083	0.84431	0.25227
2018	1.00692	1.22993	0.83524	0.28785
2019	1.0141	1.25162	0.82602	0.29466

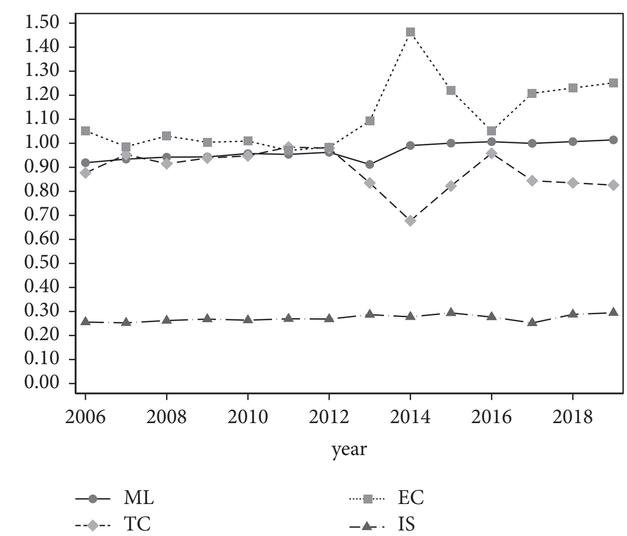

Figure 1: ML index and its decomposition terms and industrial upgrading trend.

4.2.2. Core Explanatory Variable: Industrial Structure Supererogation (IS). Industrial upgrading involves the transformation of the leading industry from the primary industry and the secondary industry to the tertiary industry, an increase in capital and technology intensity, and an increase in product added value, which reflect the trend of tertiarization. Therefore, this paper selects the ratio of the tertiary industry and the secondary industry to measure industrial upgrading. The larger the ratio is, the more obvious the effect of industrial structure upgrading is. Figure 1 shows that the trend of industrial structure upgrading (IS) is consistent with the ML index of GTFP, and it can be preliminarily judged that industrial upgrading helps to promote growth in TFP.

4.2.3. Control Variables. Due to the complexity and diversity of the influencing factors of GTFP, to make the results more robust, this paper adds control variables. These include the following:

Economic development level (PGDP): A city with high economic development has a higher investment capacity and investment level in the in-depth reform of infrastructure construction and industrial structure adjustment to promote technological innovation and the resource utilization efficiency of enterprises. In this paper, referring to Xu et al. [25], the per capita GDP of each city is used to measure regional economic development. At the same time, to verify the linear relationship between the two, the quadratic term of per capita GDP (SQPGDP) is added.

Population growth (POP): Population expansion will exacerbate energy consumption and pollutant emissions in the process of production and life, which will have an impact on GTFP. This paper uses the population growth rate (POP) to measure the population growth of each city [26].

Human capital (HC): An improvement in human capital means an enhancement of workers' knowledge reserves, labor skills, and learning ability, and the spillover effects of knowledge and technology can contribute to the growth in urban GTFP. Therefore, the number of students in regular colleges and universities is chosen as a measure in this paper [27].

Financial development (FIN): The financial sector can provide financial support for enterprises to upgrade their machinery and equipment and to invest in technology. It is also conducive to the financing of the service industry, accelerating the development of the tertiary sector, and promoting the upgrading of the industrial structure. Therefore, this paper chooses to measure the degree of financial development by the proportion of deposit and loan balances to GDP.

Population density (DENSITY): Moderate population agglomeration can help improve resource utilization efficiency and promote the development of GTFP. Therefore, this article uses the number of permanent residents per square kilometer for measurement.

Foreign direct investment (FDI): FDI can improve the technology level of a region through technology spillover effects. It can also help in learning from advanced management experience, improving the internationalization of a region, raising barriers to entry, and thus promoting the economic development of a region. Therefore, this paper chooses the proportion of FDI in GDP in each city as an indicator [28].

Table 2: Descriptive statistics of the variables.

Variable	Obs	Mean	Std. dev.	Min	Max
GTFP	3976	0.965408	0.098623	0.203	1.719
IS	3976	6.348843	0.347031	5.586918	7.472384
PGDP	3976	1.925339	0.848668	0.847942	4.191626
SQPGDP	3976	10.89733	4.621363	5.101424	21.45738
POP	3976	6.65673	4.652119	−7.2	39.18
HC	3976	1.950219	1.08839	0.45839	4.266567
FIN	3976	1.010702	0.607248	0.165491	5.065206
DENSITY	3976	2.944615	0.800503	1.789129	4.579907
FDI	3976	1.077681	0.26278	0.642084	1.380358

4.2.4. Data Sources. All data for the explained variables, core explanatory variables, and control variables are taken from the China Statistical Yearbook of Cities, the statistical yearbooks of various provinces and cities, and the Wind database. Missing data are supplemented through interpolation. The data include 284 prefecture-level cities in mainland China from 2006 to 2019, and the basic descriptive statistics of the variables are shown in Table 2.

5. Analysis of the Empirical Results

5.1. Spatial Autocorrelation Test. Prior to the spatial econometric analysis, the spatial autocorrelation test for the explanatory variables in this paper was performed using Moran's I, and the formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \tag{4}$$

where I is Moran's I, x_i is the GTFP of region i, and w_{ij} is the spatial weight matrix. The value of I is in the range [−1, 1]. When Moran's I is greater than 0, it indicates positive spatial autocorrelation of the GTFP of each region, and when it is less than 0, it indicates negative autocorrelation. In this paper, the global Moran's I is used to test the spatial correlation of GTFP. Through calculation, it is obtained that Moran's $I = 0.023$ in 2006, Moran's $I = 0.022$ in 2011, Moran's $I = 0.031$ in 2015, and Moran's $I = 0.032$ in 2019 (Figure 2), indicating that the GTFP of each city has positive spatial correlation. The number of Moran's I has continued to increase every year, indicating that the spatial agglomeration effect of GTFP has been increasing. The Moran scatter plot shows that the prefecture-level cities are mainly distributed in the first and third quadrants and that the patterns of spatial correlation are high-high agglomeration and low-low agglomeration.

5.2. Estimation Results of the Spatial Econometric Model. This paper constructs the SLM, SEM, and SDM to analyze the impact of industrial upgrading on GTFP after verifying the existence of spatial autocorrelation. The spatial weight matrices selected in this paper include the adjacent matrix ($W1$), inverse distance matrix ($W2$), economic matrix ($W3$), and economic geography nested matrix ($W4$), on the basis of which SLM, SEM, and SDM analyses are carried out. The result of the Hausman test is 0.0000, a fixed-effects model is chosen, and the results are shown in Tables 3–5.

The empirical results in Tables 3–5 show that, under the four spatial weight matrices, the direction and significance of the coefficients of the variables do not change significantly, indicating that the models are reasonable and that the reliability of the estimated results is high. Table 6 shows the diagnostic test results. Based on Elhorst's work [29], the P values of the LR test and Wald test are less than 0.01,

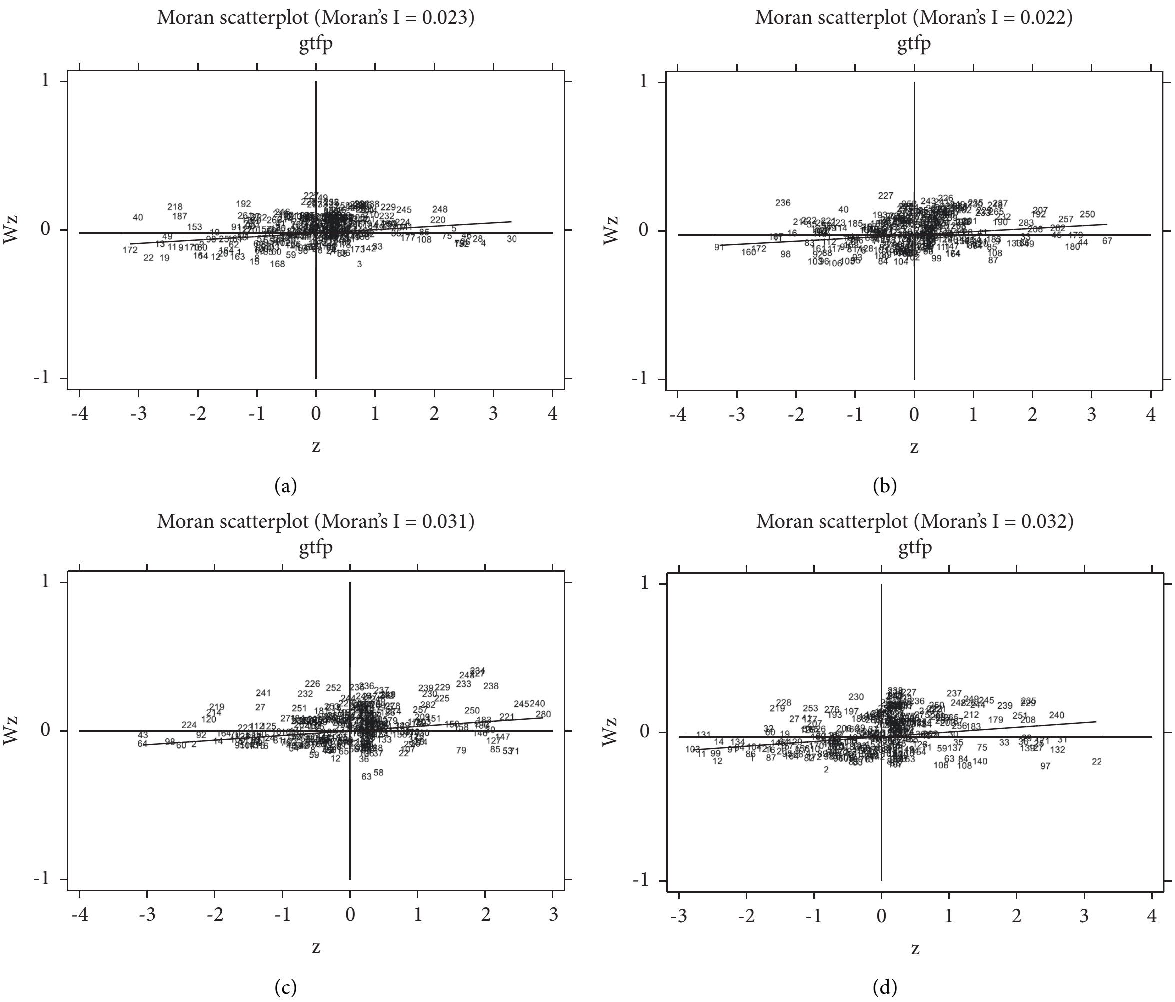

Figure 2: Moran scatter plots for 2006, 2011, 2015, and 2019. (a) 2006. (b) 2011. (c) 2015. (d) 2019.

indicating that SDM cannot be nested in the SLM. The P values of the LR test and Wald test are both less than 0.01, showing that the SDM cannot be nested in the SEM. Thus, this paper chooses to explain the estimation results of the SDM.

5.3. Impact of the Core Explanatory Variables on GTFP. The coefficient of industrial structure upgrading is significantly positive in the four spatial weight matrices and three spatial econometric models, which shows that industrial upgrading significantly promotes GTFP. The reason is that, under the background of China's transformation and structural adjustment, the overall industrial structure has changed from "2-1-3" to "3-2-1." In this process, the extensive economic development pattern of high consumption, high pollution, and high emissions has been continuously improved, and sustainable development has been continuously enhanced. At the industry level, industrial upgrading can promote the development of cleaner, pollution-free industries and raise the entry barriers of industries. At the same time, the process of industrial transformation and upgrading will increase investment in science and improve the overall technology level. At the enterprise level, the upgrading of the industrial structure will attract more technology-intensive and innovation-intensive enterprises to enter industries, reducing the intensity of consumption of resources and energy. Additionally, the division of labor among enterprises will become more refined, and each enterprise will improve its specialization and comprehensive competitiveness based on its own needs. All of this is conducive to reducing pollution emissions, promoting growth in GTFP, and improving economic quality and efficiency.

5.4. Impact of the Control Variables on GTFP. The coefficient of PGDP is positive in the four spatial weight matrices and three spatial econometric models, and it is significant at the 1% level, which shows that economic development significantly contributes to promoting GTFP. The reason for this result is that cities with high economic development have better infrastructure, a greater concentration of high-level talent, and a fuller application of advanced technologies, all of which contribute to the increase in GTFP. The negative coefficient of the quadratic term for the level of economic

Table 3: Estimated results of the SLM under four spatial matrices.

	SLM			
	(1) $W1$	(2) $W2$	(3) $W3$	(4) $W4$
IS	0.0439***	0.0178**	0.0319***	0.0320***
	(0.0127)	(0.0089)	(0.0091)	(0.0092)
PGDP	0.211***	0.163***	0.142***	0.144***
	(0.0241)	(0.0163)	(0.0169)	(0.0169)
SQPGDP	−0.0255***	−0.0226***	−0.0180***	−0.0183***
	(0.0034)	(0.0023)	(0.0024)	(0.0024)
POP	0.00000978	−0.0001	−0.0000555	$-5.92E-05$
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
HC	0.0125**	0.00631*	0.00791**	0.00808**
	(0.0052)	(0.0036)	(0.0037)	(0.0037)
FIN	0.0184***	0.00193	0.00462	0.00477
	(0.0059)	(0.0041)	(0.0042)	(0.0042)
DENSITY	0.00243	−0.0058	−0.00394	−0.00373
	(0.0121)	(0.0084)	(0.0086)	(0.0086)
FDI	−0.00769	−0.0164***	−0.0124**	−0.0122**
	(0.0078)	(0.0054)	(0.0055)	(0.0055)
Spatial				
Rho	0.172***	0.835***	0.568***	0.564***
	(0.0277)	(0.0318)	(0.0355)	(0.0355)
Variance				
Sigma2_e	0.00583***	0.00280***	0.00291***	0.00291***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	3976	3976	3976	3976
R-sq	0.091	0.151	0.175	0.174

Standard errors are in parentheses; $^{*}P<0.1$, $^{**}P<0.05$, and $^{***}P<0.01$ (the same below).

Table 4: Estimated results of the SEM under four spatial matrices.

	SEM			
	(1) $W1$	(2) $W2$	(3) $W3$	(4) $W4$
IS	0.0476***	0.0187*	0.0369***	0.0370***
	(0.0131)	(0.0108)	(0.0104)	(0.0104)
PGDP	0.226***	0.185***	0.165***	0.168***
	(0.0256)	(0.0175)	(0.0198)	(0.0196)
SQPGDP	−0.0266***	−0.0235***	−0.0190***	−0.0194***
	(0.0036)	(0.0025)	(0.0028)	(0.0028)
POP	0.0000175	−0.000202	−0.0000737	$-7.47E-05$
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
HC	0.0129**	0.00821**	0.00946**	0.00982***
	(0.0052)	(0.0037)	(0.0037)	(0.0037)
FIN	0.0187***	−0.00876*	−0.00214	−0.00168
	(0.0062)	(0.0052)	(0.0052)	(0.0052)
DENSITY	0.00274	−0.00331	−0.00264	−0.00217
	(0.0121)	(0.0085)	(0.0086)	(0.0086)
FDI	−0.00386	0.0165	0.00726	0.00737
	(0.0090)	(0.0256)	(0.0112)	(0.0111)
Spatial				
Lambda	0.160***	0.874***	0.616***	0.613***
	(0.0293)	(0.0264)	(0.0372)	(0.0371)
Variance				
Sigma2_e	0.00584***	0.00278***	0.00290***	0.00290***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	3976	3976	3976	3976
R-sq	0.088	0.159	0.154	0.153

Table 5: Estimated results of the SDM under four spatial matrices.

	SDM			
	(1) $W1$	(2) $W2$	(3) $W3$	(4) $W4$
IS	0.0259*	0.0147	0.0255**	0.0256**
	(0.0147)	(0.0110)	(0.0108)	(0.0108)
PGDP	0.145***	0.155***	0.0773***	0.0924***
	(0.0351)	(0.0185)	(0.0256)	(0.0248)
SQPGDP	−0.0153***	−0.0195***	−0.00689*	−0.00917**
	(0.0051)	(0.0026)	(0.0037)	(0.0036)
POP	0.0000854	−0.0002	0.00000681	$-9.1E-06$
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
HC	0.0122**	0.00776**	0.00879**	0.00902**
	(0.0052)	(0.0037)	(0.0037)	(0.0037)
FIN	0.00426	0.0108**	0.0106*	0.0101*
	(0.0075)	(0.0053)	(0.0055)	(0.0055)
DENSITY	0.00214	−0.004	0.00335	0.00303
	(0.0121)	(0.0085)	(0.0086)	(0.0086)
FDI	−0.00632	−0.0193***	−0.000735	−0.000722
	(0.0089)	(0.0074)	(0.0111)	(0.0130)
Spatial				
Rho	0.141***	0.811***	0.515***	0.517***
	(0.0291)	(0.0373)	(0.0399)	(0.0398)
Variance				
Sigma2_e	0.00579***	0.00279***	0.00289***	0.00289***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	3976	3976	3976	3976
R-sq	0.099	0.184	0.192	0.191

Table 6: Diagnostic test results.

Diagnostic test	λ^2	P value
LR test for the SLM	37.90	0.0000
Wald test for the SLM	25.30	0.0006
LR test for the SEM	152.8	0.0000
Wald test for the SEM	26.08	0.0010
Hausman test	54.38	0.0000

development (SQPGDP) indicates that economic development and GTFP do not have a simple linear relationship; rather, they show an inverted U-shaped relationship. The coefficient of population growth (POP) is negative but not significant, indicating that population growth does not have an agglomeration effect and only increases the consumption of resources and energy, leading to an increase in pollutant emissions. Human capital (HC) is positive and significant at the 5% level, indicating that human capital contributes to GTFP. The significant knowledge and externalities effect of human capital can improve the management and technology level of cities and companies, thus contributing to high-quality development. The coefficient of financial development (FIN) is positive and significant, indicating that financial development can contribute to GTFP through strong financial support. Population density (DENSITY) is negative but not significant test, as there is a large disparity in population density in Eastern, Central, and Western China, resulting in a nonsignificant increase in GTFP. The coefficient of foreign direct investment (FDI) is negative but not significant test. This result is due to the lack of effective

Table 7: Estimated results for regional heterogeneity—eastern region.

	SDM			
	(1) $W1$	(2) $W2$	(3) $W3$	(4) $W4$
IS	0.0366***	0.0222**	0.0231**	0.0392***
	(0.0089)	(0.0086)	(0.0106)	(0.0104)
PGDP	0.199***	0.198***	0.152***	0.211***
	(0.0313)	(0.0298)	(0.0387)	(0.0343)
SQPGDP	−0.0245***	−0.0269***	−0.0187***	−0.0237***
	(0.0045)	(0.0043)	(0.0057)	(0.0048)
POP	0.000478	0.000266	0.000426	0.000361
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
HC	0.00621	0.00528	0.00692	0.00701
	(0.0062)	(0.0061)	(0.0063)	(0.0062)
FIN	0.0142**	0.00903	−0.00401	0.0113
	(0.0070)	(0.0068)	(0.0090)	(0.0085)
DENSITY	0.0148	0.0135	0.0133	0.0183
	(0.0119)	(0.0115)	(0.0120)	(0.0121)
FDI	−0.00329	−0.0106	−0.00605	0.0229
	(0.0098)	(0.0095)	(0.0120)	(0.0164)
Spatial				
Rho	0.454***	0.734***	0.121***	0.470***
	(0.0512)	(0.0493)	(0.0405)	(0.0614)
Variance				
Sigma2_e	0.00284***	0.00269***	0.00286***	0.00288***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	1400	1400	1400	1400
R-sq	0.284	0.26	0.179	0.256

Table 8: Estimated results for regional heterogeneity—central region.

	SDM			
	(1) $W1$	(2) $W2$	(3) $W3$	(4) $W4$
IS	0.0434***	0.0419***	0.0451***	0.0455***
	(0.0118)	(0.0120)	(0.0116)	(0.0116)
PGDP	0.0772*	0.172***	0.193***	0.209***
	(0.0428)	(0.0344)	(0.0340)	(0.0365)
SQPGDP	−0.0110*	−0.0268***	−0.0265***	−0.0270***
	(0.0062)	(0.0049)	(0.0049)	(0.0053)
POP	0.00120**	0.000932	0.00151***	0.00152***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
HC	0.0203***	0.0208***	0.0173**	0.0171**
	(0.0067)	(0.0067)	(0.0068)	(0.0067)
FIN	−0.0421***	−0.0315***	0.00475	−0.00192
	(0.0107)	(0.0103)	(0.0074)	(0.0088)
DENSITY	0.0405	0.0476	0.0132	0.0224
	(0.0432)	(0.0436)	(0.0436)	(0.0439)
FDI	0.00241	0.00452	−0.0451***	−0.0461***
	(0.0021)	0.0052	(0.0108)	(0.0135)
Spatial				
Rho	0.420***	0.529***	0.211***	0.251***
	(0.0694)	(0.0862)	(0.0449)	(0.0495)
Variance				
Sigma2_e	0.00304***	0.00303***	0.00328***	0.00326***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	1162	1162	1162	1162
R-sq	0.083	0.144	0.109	0.096

Table 9: Estimated results for regional heterogeneity—western region.

	SDM			
	(1) $W1$	(2) $W2$	(3) $W3$	(4) $W4$
IS	0.0657***	0.0593***	0.0597***	0.0657***
	(0.0145)	(0.0144)	(0.0149)	(0.0145)
PGDP	−0.0126	−0.0269	−0.0301	−0.0126
	(0.0431)	(0.0335)	(0.0464)	(0.0431)
SQPGDP	−0.000231	$-9.9E-05$	0.00116	−0.00023
	(0.0056)	(0.0043)	(0.0060)	(0.0056)
POP	−0.00110**	−0.00116**	−0.00108**	−0.00110**
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
HC	0.000643	−0.00079	0.00777	0.000643
	(0.0061)	(0.0061)	(0.0063)	(0.0061)
FIN	0.0368***	0.0276***	0.0382***	0.0368***
	(0.0085)	(0.0089)	(0.0078)	(0.0085)
DENSITY	−0.0304**	−0.0288**	−0.0240*	−0.0304**
	(0.0123)	(0.0121)	(0.0128)	(0.0123)
FDI	0.0203**	0.0176*	$-2.5E-05$	0.0203**
	(0.0097)	(0.0100)	0.0000	(0.0097)
Spatial				
Rho	0.584***	0.746***	0.303***	0.584***
	(0.0496)	(0.0472)	(0.0395)	(0.0496)
Variance				
Sigma2_e	0.00224***	0.00216***	0.00242***	0.00224***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	1414	1414	1414	1414
R-sq	0.066	0.032	0.038	0.066

screening for the introduction of foreign-funded enterprises in China's opening-up process and the entry of high-polluting, low-value-added enterprises, which hinders the improvement in GTFP.

5.5. Regional Heterogeneity Test. Considering the vast geographical area of China, there are large differences in the initial factor endowment, economic base, and policy support of different regional cities. Hence, there are large differences in the impact of industrial upgrading on GTFP in each city, and the positive and negative effects easily offset each other, thus leading to deviations in the overall effect. Therefore, this paper divides the 284 prefecture-level cities into eastern, central, and western regions by geographical location for split-sample regression, including 92 eastern cities, 78 central cities, and 48 western cities. The results of the regional heterogeneity test are shown in Tables 7–9.

According to the regression results, under the $W1$, $W2$, $W3$, and $W4$ matrices, the regression coefficients of the SLM, SEM, and SDM are positive and significant, indicating that industrial upgrading can significantly promote GTFP in the eastern, central, and western regions. However, the regression coefficient of industrial upgrading in the western region is larger than that in the central region, and that in the central region is greater than that in the eastern region.

The reason is that, in the process of reform and opening up, the eastern region took the lead in realizing industrial structure upgrading, and the structural dividend enabled it

Table 10: Robustness test results.

	(1) SDM	(2) SDM	(3) GMM
L.GTFP			0.243***
			(0.0138)
IS	0.0266**		0.101***
	(0.0124)		(0.0145)
IS2		0.0743**	
		(0.0289)	
PGDP	0.0811***	0.595***	0.654***
	(0.0257)	(0.1350)	(0.0582)
SQPGDP	0.00830**	0.0929***	0.0931***
	(0.0036)	(0.0193)	(0.0084)
POP	$5.07E-05$	0.00145	0.00223***
	(0.0003)	(0.0015)	(0.0005)
HC	0.00853**	−0.0214	−0.00679
	(0.0037)	(0.0191)	(0.0122)
FIN	−0.00774	−0.00536	0.0428***
	(0.0055)	(0.0282)	(0.0068)
DENSITY	−0.0024	0.0114	0.0194
	(0.0086)	(0.0443)	(0.0131)
FDI	−0.00077	0.108***	−0.0175***
	(0.0072)	(0.0375)	(0.0054)
Spatial			
Rho	0.468***	0.947***	
	(0.0414)	(0.0080)	
Sigma2_e	0.00288***	0.0772***	
	(0.0001)	(0.0018)	
AR(2)			0.119
Hensen			0.238
N	3976	3976	3692
R-sq	0.121	0.435	

to realize a synergy of economic development and environmental protection. Over time, however, the advantage of the structural dividend has been shrinking, so the promoting effect of industrial upgrading on GTFP is the lowest. The central region focuses on developing a high-quality manufacturing industry and improving the independent innovation capacity in key fields. The western region actively undertakes industrial transfer from the central and western regions and gives full play to its late-mover advantages, so the promoting effect of industrial upgrading on GTFP is the most obvious.

5.6. Robustness Test. To verify the credibility of the results, this paper carries out robustness analysis based on the three following aspects. First, this paper takes the work of Wu et al. [30] for reference and uses the GML index to recalculate GTFP. The empirical results are shown in the first column of Table 10. Second, drawing on the practice of Su and Fan [31], this paper constructs indicators of industrial structure rationalization, and the empirical results are shown in the second column. Finally, this paper uses the GMM model to test the dynamic impact of industrial upgrading on GTFP, which is also helpful in solving endogeneity problems. The empirical results are shown in the third column of Table 10. The empirical conclusions of this paper remain robust, which further verifies the credibility of the benchmark regression.

6. Conclusions and Policy Recommendations

This paper uses panel data covering 284 prefecture-level cities in China to measure their GTFP and empirically analyzes the impact of industrial structure upgrading on GTFP by constructing a spatial econometric model. It mainly draws the following conclusions: (1) Overall, the GTFP in China's prefecture-level cities shows a fluctuating upward trend and exhibits a significant spatial spillover effect. (2) From the results of the full sample analysis, industrial upgrading can significantly promote the development of GTFP. Regarding the control variables, GTFP and economic development have an inverted U-shaped relationship, with human capital and financial development playing a driving role in TFP, while population density plays a suppressing role. (3) From the subsample regression results, industrial upgrading in the eastern, central, and western regions can significantly contribute to growth in GTFP, with the strongest promoting effect in the western region, followed by the central region; the promoting effect in the eastern region is the weakest. Based on these findings, this paper proposes the following policy recommendations.

6.1. Grasping the Direction of Industrial Upgrading and Optimization to Achieve Green Economic Growth. Industrial upgrading and adjustment should aim to grow green economic benefits, reduce the dependence on resource-based industries, accelerate the transition to emerging industries and service industries, and promote the growth of the regional green economy in various ways. For labor-intensive industries, we should introduce new and high technology as well as advanced machinery and equipment to enhance the technical efficiency and production efficiency of industries and promote the evolution of low-level industries to high technology. For resource-intensive industries, it is necessary to develop and use resources reasonably among industries, coordinate the use of new technologies among industries, promote the scale efficiency of industrial production, and promote the overall upgrading of the three industrial structures. For capital-intensive industries, we should adopt the dual concepts of increasing economic benefits and reducing environmental pollution emissions, cultivate capital-intensive industries with green economic development prospects, and improve the service quality of these industries to maximize the efficiency of the green economy.

6.2. Multipronged Approach to Achieving Green Economic Development. Improving human capital is an important link in improving green total factor productivity. We should strengthen the talent strategy, cultivate innovative talent, increase investment in human capital, improve the talent incentive mechanism, provide a broader platform for human capital to play its role, and increase the return on human capital investment. We should also give full play to finance in GTFP, implement flexible and sustainable financial industry policies, actively guide the flow of financial resources to industrial enterprises with high efficiency and cleaner production, optimize the allocation of funds, and comprehensively improve GTFP.

6.3. Formulating Differentiated Industrial Policies Based on Local Conditions. For the eastern region, we should further optimize resource allocation based on its advantages, follow the objective law of economic service development, adhere to the development direction of high-end, intelligent, and green industry, and constantly improve the efficiency of industrial green production. For the central region, we should continue to maintain the advantages of eco-friendly leading industries and provide corresponding policy support to further improve the technological content of leading industries. For the western region, we should promote the technological upgrading of traditional industries, promote the close combination of high technology and the informatization of the manufacturing industry, realize the transformation and upgrading of the economic development mode, and then promote green economic development.

Data Availability

The data used to support the findings of this study were supplied by Tao Ma under license and so cannot be made freely available. Requests for access to these data should be made to tiangongmt@126.com.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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