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Research article

Analysis of the impact factors of industrial structure upgrading on green total factor productivity from the perspective of spatial spillover effects

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A R T I C L E I N F O

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A B S T R A C T

Green development has already been a vital part of China's high-quality economic progress in the future, and accelerating the restructuring and improvement of the industrial structure plays a crucial roll in promoting a regional green economy. In this article, based on the data of 278 prefecture-level cities in China from 2011 to 2020, the SBM directional distance function and Malmquist-Luenberger (ML) index are used to gauge regional green total factor productivity (GTFP). The spatial Durbin model is also introduced to investigate the spatial spillover mechanism of GTFP and its influencing factors under the optimized and upgraded industrial structure. The study indicates that the optimization of the industrial structure have an important effect in promoting the growth of GTFP. Specifically, industrial structure integration has a greater bearing on the increase in GTFP, while there is a difference in the effectiveness of industrial structural advancement and rationalization of GTFP. Economic growth level inhibits the enhancement of GTFP, and urbanization level and industrial agglomeration have a significant negative impact on the enhancement of GTFP in the spatial dimension. On a different hand, foreign investment degree and government intervention level have a significant positive affect on regional GTFP. In addition, this study fills the research gap of the regional industrial structure upgrading influence on GTFP, which has great theory and practice value for promoting China's high quality growth of green economy.

1. Introduction

With the rising prominence of global environmental problems, green and sustainable development have become an important direction for policymaking and industrial transformation in countries around the world. While promoting economic growth, the realization of green development is crucial to achieving greater efficiency in the use of resources, decreasing environmental pollution and protecting the ecosystem. Industrial structure, as the basis of economic operation, has a significant implication for green total factor productivity (GTFP). Therefore, vigorously developing emerging industries, realizing industrial transformation and upgrading, and promoting high-quality economic growth have become critical issues that China's regional development must address.

Scholars' research on industrial structure mainly focuses on the features of industrial change, evolutionary path [1–3], economic contribution [4–6], and the influence of external factors such as environmental regulation, urbanization, and foreign investment [7–9].

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However, among these studies, an in-depth exploration of regional industrial structure differences due to spatial spillover effects is still relatively lacking. In particular, under different conditions of geographic environment and resource distribution, there are significant regional characteristics of the influence of industrial structure on the level of development of each region [10]. In addition, compared with the traditional total factor productivity (TFP) measure, the GTFP covers both desired and undesired outputs, which integrates economic and environmental interests, and aims to realize the coordinated development of economics and eco-systems. In studying evaluation methods, Pittman [11] introduced non-expected outputs within the DEA framework. Based on this, Chung et al. [12] and Fare et al. [13] extended the framework by proposing the Directional Distance Function (DDF) and the ecologically compatible Malmquist Luenberger (ML) index. Following this, Kumar [14] demonstrated the utility of the ML index in his analysis of GTFP in different countries, as well as Wang et al. [15] and Huang et al. [16] in their analysis of industrial GTFP in China. However, these assessments usually rely on radial and angular methods, which can lead to measurement bias. To address this issue, Fukuyama [17] proposed an advanced SBM directional distance function based on the non-radial and non-rectangular methods of Tone [18], which gained academic popularity. Subsequently, Oh [19] addressed the limitations of the ML index by forming a full-domain production possibility set and introducing a generalized Malmquist Luenberger (GML) index. Recently, researchers such as Zhou [20], Liu [21], and Zhang [22] fused these methods together by applying the GML index and the SBM direction function to measure GTFP more efficiently.

Concerning the effects of changes in industrial structure on GTFP, existing studies focus on three primary areas: First, the beneficial impacts of industrial upgrading on GTFP: research has consistently shown that the modernization of industrial structures fosters better resource allocation and boosts environmental efficiency, thus enhancing GTFP [23,24]. For instance, Noseleit [25] analyzing German data spanning 1975–2002, concluded that sectoral redistribution significantly propels economic growth. Further evidence from Japan's economy by Fukao and Paul [26] showed that trade and services have been central to GDP growth in the last century. Similarly, findings from Zhang [27], Jin [28], Yang [29], Xu [30], and Sun [31] corroborate the positive influence of industrial upgrading on GTFP through empirical analysis. Second, the adverse consequences of industrial transition (known as the "structural burden hypothesis"): During the upgrading phase, the emergence of new industries and decline of old ones might, in the short-term, impose strains on GTFP [32]. Studies by Wang et al. [33] identified a drop in GTFP due to the reorganization of the tertiary sector, particularly in industries with varying pollution levels. Additionally, the expansion of economically less beneficial service sectors can paradoxically reduce productivity [34], while excessive shifts towards service-oriented structures might slow economic momentum [35]. Third, the variable impacts of industrial restructuring on GTFP: It has been observed that industrial structure adjustments can exert both positive and negative effects on GTFP, which introduces complexity and has become a focal point of new studies. Wang et al. [36] demonstrated the dual impacts of industrial change on comprehensive and biased green technological advancements. Guo et al. [37] explained that urban industrial progress boosts GTFP heterogeneously across different stages of development. Lee [38] established that industrial structure rationalization is favorable to GTFP, yet there exists regional variation in this progress. Finally, Sun et al. [39] indicated that advanced industrial structures promote GTFP but the effect of rationalization alone is inconsequential.

In summary, the existing studies have been fruitful in measuring the development status of GTFP and analyzing its influencing factors, which provide strong support for this paper. However, there are insufficient studies on the spatial efficiency of the affects of industrial structure upgrading on GTFP in China; meanwhile, studies on the correlation between industrial structure and GTFP show inconsistent results, which may be related to the fact that industrial structure is too broadly categorized; in addition, insufficient attention has been paid to what role environmental pollution factors play in GTFP measurement. Improving these deficiencies against the needs of China's green development strategy, especially when environmental pollution is considered as a measurement criterion, is more in line with the requirements of high-quality growth of green economy. In comparison with previous studies, there exists the presence of the below extensions to this paper: (1) A sample of 278 prefecture-level cities is selected for this study to explore in more detail the spatial spillovers of regional industrial structure upgrading and their impact on GTFP. (2) For the linkage between industrial structure upgrading and GTFP, a finer distinction of industrial structure is made by refining it into three parts: integration, rationalization and advancement, which helps to reveal this complex relationship. (3) Regarding the research methodology, this paper measures regional GTFP based on the GML index of the SBM directional distance function, and combines, Spatial Durbin Model and other advanced econometric methods to provide stronger scientific support for the analysis. This paper provides a theoretical and methodological supplement to the above research gaps, which not only facilitates an in-depth understanding of the complex relationship that exists among industrial structure upgrading and GTFP, but also provides empirical support for China's green development and high-quality economic growth policies.

2. Research design and data sources

2.1. Construction of spatial weight matrix

Despite the fact that there are now three separate forms of spatial weight matrices—spatial adjacency, economic distance, and geographic distance—the variables affecting various areas are not just dependent on geographic distance. Economic remoteness is also quite important. In order to more accurately measure the breadth and complexity of spatial impacts, this effort combines the inverse distance weight matrix with an economic feature weight matrix.

First, construct a spatial inverse distance weight matrix, see Eq. (1):

$$W_{ij}^{G}=\begin{cases}\dfrac{1}{d^{2}}, i\neq j\\ 0, i=j\end{cases} \tag{1}$$

Create an economic distance matrix next. This research uses a strategy that is often used in the academic community, which is to take the average of economic indicators across the period under consideration since the economic difference between two areas changes with time. In this research, the economic distance matrix is created using GDP as the economic indicator between two areas, as detailed in Eq. (2):

$$W_{kj}^{E}=\begin{cases}\dfrac{1}{\left|\overline{X}_{i}-\overline{X}_{j}\right|}, i\neq j\\ 0, i=j\end{cases} \tag{2}$$

As shown in Eq. (3), the economic distance weight matrix and the geographic distance weight matrix are combined to create a nested matrix. The value of φ is obtained through computer simulation, and the optimal value is found to be 0.5. Following the processing principles of numerous articles, φ is set to 0.5, and the final nested weight matrix is obtained:

$$W_{\varphi=0.5}=0.5*W^{G}+0.5*W^{E} \tag{3}$$

2.2. Construction of spatial econometric model

According to the previously established mechanism, industrial structure upgrading and GTFP are considered to have strong spatial correlation. Neglecting the spatial spillover effect will bring bias to the panel regression model. Consequently, this paper constructs a spatial Durbin model for empirical study drawing on Elhorst [40], see Eq. (4). The model includes spatial lag terms for industrial structure upgrading and GTFP, aiming to capture the spatial correlation of variables more accurately.

$$\begin{aligned}lnGTFP_{it}=&\rho WlnUIS_{it}+\beta_{1}lnPGDP_{it}+\beta_{2}lnUR_{it}+\beta_{3}\ln IA_{it}+\beta_{4}lnFDI_{it}+\beta_{5}lnGOV_{it}+W(\eta_{1}lnPGDP_{it}\\&+\eta_{2}lnUR_{it}+\eta_{3}\ln IA_{it}+\eta_{4}lnFDI_{it}+\eta_{5}lnGOV_{it})+u_{i}+v_{i}+\varepsilon_{it}\end{aligned} \tag{4}$$

In this framework, GTFP serves as the explanatory variable while UIS serves as the core explanatory variable. The control variables, namely PGDP, UR, IA, FDI and GOV, correspond to the economic development status, urbanisation rate, industrial concentration, FDI level and government influence size, respectively. Coefficients of the model are α, β1, β2, β3, β4, β5 and β6, and the economic-geographical nested matrix used in the model is denoted by letter W. Additionally, " i " denotes different regions and " t " denotes the year. The former is denoted by the symbol υ and the latter by the symbol v. "ε" is used to denote the random error component in the model.

2.3. Variables

2.3.1. Dependent variables

As discussed in the literature review, for the GTFP measure, the SBM directional distance function and the GML metrics do improve on the limitations of earlier research methods in terms of incorporating slack. Nonetheless, the SBM is still deficient in dealing with inconsistencies in the production unit frontiers in a uniform manner across periods, something that affects the comparability of results across periods. At the same time, the GML metrics applied in isolation failed to address measurement bias due to radial and angular differences. In contrast, when the GML metric is combined with the SBM directional distance function, it is able to robustly address these issues and ensure comparative consistency of production frontiers on a global scale. In view of this, some recent studies [20–22] have begun to effectively integrate these two approaches and use GML metrics derived from the SBM directional distance function to more accurately assess GTFP, which is the approach followed in this study to ensure accurate measurement of GTFP.

The production possibility set for each city may be observed in Eq. (5) under the assumption that each city is an autonomous production decision-making unit, employing k kinds of input components $x\in R^{+}{}_{k}$, m types of anticipated output $y\in R^{+}{}_{m}$, and n types of non-expected output $z\in R^{+}{}_{n}$.

$$P^{G}(x)=P^{1}\left(x^{1}\right)\cup\cdots\cup P^{T}\left(x^{T}\right) \tag{5}$$

Using the DEA (Data Envelopment Analysis) method (Eq. (6)), it is further obtained that:

$$P^{G}(x^{t})=\left\{\left(y^{'},z^{t}\right):\sum_{t=1}^{T}\sum_{i=1}^{t}\lambda_{i}^{t}y_{im}^{'}\geqslant y_{im}^{t};\sum_{t=1}^{T}\sum_{i=1}^{t}\lambda_{i}^{t}z_{in}^{t}=z_{in}^{t};\sum_{t=1}^{T}\sum_{i=1}^{t}\lambda_{i}^{t}x_{ik}^{'}\leqslant x_{ik}^{t};\sum_{i=1}^{l}\lambda_{i}^{t}=1\right\} \tag{6}$$

Where i and t stand for the region and year, respectively, and λ^{t} for the weight, $\Sigma_{i=1}^{I}\lambda_{t}^{i}=1$ indicates varying returns to scale during the production process. The manufacturing process has continuous returns to scale if there are no such limiting conditions. According to Fukuyama and Weber's [17] research, this study calculates the SBM directional distance function based on Eq. (7):

$$S_V^G = \left(x^{i,t}, y^{i,t}, z^{i,t}, g^x, g^y, g^z\right) = max\left[\frac{1}{K}\sum_{k=1}^{K}\frac{s_k^x}{g_k} + \frac{1}{M+1}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{n=1}^{N}\frac{s_n^z}{g_n}\right)\right] \Big/ 2$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}\lambda_i^t x_{ik}^t + s_k^x = x_{ik}^t, \forall k; \sum_{t=1}^{T}\sum_{i=1}^{t}\lambda_i^t y_{im}^t - s_m^x = y_{im}^t, \forall m; \sum_{t=1}^{T}\sum_{i=1}^{I}\lambda_i^t Z_{in}^t + s_n^x = z_{in}^t, \forall n; \tag{7}$$

$$s.t.\ \sum_{i=1}^{I}\lambda_i^t = 1, \lambda_i^t > 0; s_k^x \geqslant 0, \forall k; s_m^y \geqslant 0, \forall m; s_n^z \geqslant 0, \forall n$$

The input, anticipated output, and unexpected output for city i in period t are all represented in this equation by ($x^{i,t}$, $y^{i,t}$, $z^{i,t}$), respectively. (g^x, g^y, g^z) stand for decreasing inputs, raising anticipated outputs, and decreasing unexpected outputs, in that order. Slack vectors (s^x, s^y, s^z) each reflect an excess of inputs, an absence of anticipated outputs, and an abundance of unexpected outcomes.

$$GML_t^{t+1} = \frac{1 + S_V^G(x^{t+1}, y^{t+1}, z^{t+1}; g)}{1 + S_V^G(x^t, y^t, z^t; g)} \tag{8}$$

Since the GML index, as measured by Eq. (8), is a relative metric, a value larger than 1 denotes an increase in the index, while a value lower than 1 indicates a decrease. Capital, employment, and total societal electricity consumption are among the input indicators. This acrticle using the perpetual inventory approach, the capital stock K is determined as shown in Eq. (9):

$$Kit = (1 - \delta)Kit - 1 + Iit \tag{9}$$

Here, I_{it} represents the fixed asset investment amount; the capital depreciation rate δ is 9.6%; and total energy consumption is measured using the annual electricity consumption in society. The expected output indicator is real GDP, while the non-expected output indicators are wastewater, SO_2, and dust emissions.

2.3.2. Core explanatory variables

In order to comprehensively understand industrial structure upgrading and explore the different degrees of influence of different industrial structures on GTFP, this study follows the research method of Wang et al. [41], which classifies industrial structure into integration of industrial structure, rationalization of industrial structure and advanced industrial structure. The association between industrial structure upgrading and GTFP is analysed extensively and in detail from three different industrial structure perspectives.

(i) The industrial structure's integration index. The three industries' output value structures have changed, indicating the degree of coordinated growth among them, and are included in the overall upgrading of the industrial structure. The three industries are given varying weights, and the weighted total is then calculated to provide an index of overall coordination and upgrading of the industries, which roughly corresponds to the overall degree of structural upgrading of the three industries. Eq. (10) is the precise calculation formula:

$$UIS_1 = \sum_{n=1}^{3} s_n \times n, 1 \leq IS_1 \leq 3 \tag{10}$$

Here, "s_n" denotes the proportion of an industry's output value that it makes up, and "UIS_1" stands for the coefficient of industrial structural upgrading as a whole that this article is interested in.

(ii) The industrial structure's indicator of rationalization. The evaluation of industrial structure is being done in academia using a variety of methodologies. The assessment of rationalization of industrial structure, however, continues to primarily center on resource allocation, which is the accepted methodology. This indicator is mainly used to measure how resource factors are distributed, coordinated, and employed across sectors. In order to measure the rationalization of industrial structure, Han [42] employed the degree of correlation between input structure and output structure. Thus, the industrial structure's deviation is calculated as shown in Eq. (11):

$$E = \sum_{i=1}^{3}\left|\frac{(Y_i/L_i)}{(Y/L) - 1}\right| = \sum_{i=1}^{3}\left|\frac{(Y_i/Y)}{(L_i/L) - 1}\right| \tag{11}$$

Then, based on the aforementioned industrial structure deviation degree, a new index is created to measure the rationalization of industrial structure, as shown in Eq. (12):

$$UIS_2 = -\sum_{i=1}^{3}(Y_i / Y)\left|\frac{(Y_i/L_i)}{(Y/L)} - 1\right| \tag{12}$$

In this equation, Y stands for output, L for labor input, and i for the i-th sector. The updated approach not only incorporates the benefits of the first deviation calculation for industrial structure but also takes output weighting into account to represent the relative significance of each sector. When UIS_2 is used to quantify the level of industrial organization rationalization, the lower the result, the more irrational it is, and vice versa.

(iii) The industrial structure's indicator of advanced. The term "advanced industrial structure" is mostly used to explain how the proportionate connection between industries has changed and how worker productivity efficiency has increased. The angle measuring technique suggested by Xiao [43] is currently used to measure this index mostly experimentally, and this study also makes reference to this algorithm. This is the precise measuring technique: A collection of three-dimensional vectors, $X_0=(X_{1,0}, X_{2,0}, X_{3,0})$, is produced by first splitting the GDP into three equal halves, each one determined by one of the three industries. Next, a component of the spatial vector is obtained from the ratio of each component's value to GDP. The angle between the unit vectors of the three industries is then computed (Eq. (13)):

$$\theta = Arccos \frac{\sum_{i=1}^{3}\left(x_{i,j}\cdot x_{i,0}\right)}{\left(\sum_{i=1}^{3}x_{i,j}^{2}\right)^{1/2}\cdot\left(\sum_{i=1}^{3}x_{i,0}^{2}\right)^{1/2}} \tag{13}$$

The following definition provides the formula used to calculate the index of industrial structure advancement (Eq. (14)):

$$UIS_3 = \sum_{k=1}^{3}\sum_{j=1}^{k}\theta_j \tag{14}$$

According to the aforementioned calculation, generally speaking, the degree of industrial structure optimization increases with increasing UIS_3 values.

2.3.3. Control variables

When examining how industrial structure upgrading influences GTFP, the following factors are used as control variables to account for the impact of other variables.

(i) Level of economic development. The measure of economic development used in this article is the per capita gross domestic product (PGDP). This is due to the fact that, to some degree, per capita GDP serves as a proxy for the region's "factor endowment" [44]. Furthermore, there is a strong correlation between environmental contamination and each region's economic progress. Therefore, it is crucial to take into account how economic growth may affect GTFP. To account for pricing concerns, the figures are modified using 2004 as the base year and the per capita GDP price index.

(ii) Urbanization rate (UR). Although the rise in urban population benefits economic growth, it also has a negative influence on the environment [45]. Increasing urbanization is strongly tied to the growth of the green economy, which may stimulate efficient resource use, create eco-friendly cities, support technical advancement and industrial modernization, and promote sustainable development. The urbanization rate is often calculated as the urban population divided by the total population in each prefecture-level city.

(iii) Agglomerations of industries (IA). A location's level of industrial agglomeration may be a reliable sign of how established its lucrative industries are. The main way to promote green economic growth and industrial agglomeration is to increase the level of coordinated industry development [46]. This article employs the location quotient to quantify the degree of geographical concentration of the industrial industry because it provides a more accurate representation of the degree of industrial agglomeration.

(iv) Foreign direct investment (FDI). In addition to promoting economic growth and improving energy consumption efficiency while lowering pollutant emissions, an increase in foreign direct investment may strengthen local technical innovation capacity [47]. This article measures the extent of regional investment attractiveness using the actual amount of foreign investment.

(v) Government intervention capability (GOV). Government intervention involves the deployment of suitable administrative measures to address flaws in the way the market mechanism functions. It may help the market economy allocate resources in the

Table 1
Descriptive statistical analysis of variables.

	Variable	Obs	Mean	Std. Dev.	Min	Max
Explained variables	Green Total Factor Productivity(GTFP)	2780	1.608	0.424	0.713	2.837
Core explanatory variables	Industrial structure integration (UIS_1)	2780	2.381	0.124	2.133	2.827
	Industrial structure rationalization (UIS_2)	2780	0.529	0.287	0.016	1.411
	Industrial structure advanced (UIS_3)	2780	1.264	0.702	0.527	5.234
Control variables	Level of economic development (PGDP)	2780	10.761	0.625	7.213	12.465
	Urbanization rate (UR)	2780	0.592	0.122	0.352	0.896
	Industry aggregation (IA)	2780	0.102	1.171	−0.692	6.033
	Foreign direct investment (FDI)	2780	0.021	0.019	0	0.121
	Government intervention capability (GOV)	2780	0.246	0.102	0.106	0.628

most efficient way possible, furthering the promotion of economic development [48]. The share of fiscal spending in each area is used in this article to gauge the capacity of the government to intervene.

2.4. Data sources

The data's source can be identified using the "China Urban Statistical Yearbook," regional statistical yearbooks, and the CSMAR database. Based on the reliability and accessibility of the data, the relevant information for 278 prefecture-level cities in mainland China from 2011 to 2020 was selected for empirical analysis. Table 1 displays the descriptive information from the research.

3. Results and discussion

3.1. Spatial correlation test

3.1.1. Global Moran's I

Spatial autocorrelation, also known as spatial correlation or spatial dependence, refers to the degree to which adjacent or nearby geographic locations are similar in their attributes or characteristics.

Based on the complexity of spatial autocorrelation, the spatial matrix described above is introduced in this paper to perform spatial correlation tests. The calculation formula is shown in Eq. (15) and Eq. (16):

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_i(Y_i-\overline{Y})(Y_j-\overline{Y})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{15}$$

Among them:

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i-\overline{Y}), \overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i \tag{16}$$

Here, the index Y_i is used to measure the upgrading of the industrial structure in region i, while W_{ij} is a matrix that represents the economic distance between regions. Moran's I is a statistical measure that quantifies spatial autocorrelation and takes values between −1 and 1. A value greater than 0 indicates positive spatial autocorrelation, while a value less than 0 indicates negative spatial autocorrelation. A value of 0 indicates no spatial correlation.

By calculating Moran's I statistic, the similarity of sample observations in neighboring spatial regions can be assessed. The outcome of the global spatial autocorrelation test in Table 2 shows that GTFP, industrial structure integration, rationalization, and advancement all exhibit significant positive spatial correlation, and demonstrate significant demonstration effects and a certain degree of spatial agglomeration distribution throughout the study area. In addition, regional GTFP also has significant spatial spillover effects on surrounding areas. Therefore, using spatial econometric methods for research is rational and effective.

3.1.2. Local Moran's I

The level of correlation between the values of a geographic unit and those of its neighboring unit is indicated by the local Moran's I. The relationship between the research items in all spatial units within the study region is better described by local Moran's I as opposed to global Moran's I. The local Moran's I is calculated as shown in Eq. (17):

Table 2
GTFP and the Moran index of industrial structural upgrading.

Variables	GTFP		UIS_1		UIS_2		UIS_3	
Year	I	p-value*	I	p-value*	I	p-value*	I	p-value*
2011	0.405	0.000	0.285	0.000	0.285	0.000	0.401	0.000
2012	0.365	0.000	0.034	0.065	0.279	0.000	0.409	0.000
2013	0.207	0.003	0.218	0.000	0.275	0.000	0.407	0.000
2014	0.257	0.005	0.214	0.000	0.274	0.000	0.396	0.000
2015	0.198	0.019	0.218	0.000	0.276	0.000	0.381	0.000
2016	0.197	0.019	0.203	0.000	0.127	0.000	0.369	0.000
2017	0.196	0.020	0.201	0.000	0.275	0.000	0.350	0.000
2018	0.284	0.002	0.193	0.000	0.289	0.000	0.325	0.000
2019	0.250	0.006	0.131	0.000	−0.006	0.116	0.311	0.000
2020	0.220	0.000	0.258	0.000	0.300	0.000	0.216	0.000

Note: *,**, and *** indicate the significance level, respectively, at 10%, 5% and 1%.

$$I_i = \frac{(y_i - \bar{y})}{S^2} \sum_{j=1}^{n} w_{ij}(y_j - \bar{y}) \tag{17}$$

In this paper, scatter plots of regional GTFP and industrial structure are plotted separately as follows in an effort to visualize the local Moran's index.

The local Moran's scatter plots in Figs. 1–4 represent the spatial distribution of GTFP, industrial structure integration, industrial structure rationalization, and advanced industrial structure in 2020. The majority of scatter points are located in the first and third quadrants, indicating a strong positive spatial correlation between these variables across various regions. To this end, a spatial econometric model can be applied to analyze the impacts of regional industrial structure upgrading on GTFP.

3.2. Formal test of model setting

The choice of spatial econometric models is made after testing for geographic correlation using the LM, LR, Wald, and other tests. A "from specific to general" and "from general to specific" testing strategy is used in this article. The LM and robustLM tests are then coupled with the LR and Wald tests to see whether the SDM model can be divided into SLM or SEM models. Depending on the outcome of the Hausman test, fixed or random effects are then selected. If a model with fixed effects is selected, tests to establish whether the fixed effects should be time, space, or both are then used.

In order to decide which geographical regression model is best, the LM test is used to assess the effectiveness of several spatial econometric models by examining the significance of the estimated values. According to the information in Table 3, the Lmlag estimate is 23.421, the R-Lmlag estimate is 23.200, the Lmerr observation value is 21.104, and the R-Lmlag observation value is 22.031. All of these values pass the significance test at a 1% level. Therefore, the model is initially set as an SDM model, and a related test is conducted to see if it can be degraded into SAR or SEM models.

From the estimation results in Tables 3 and it can be concluded that both WaldSpatial-lag and LRSpatial-lag estimates, as well as WaldSpatial-error and LRSpatial-error estimates, are highly significant and reject the null hypothesis. The Hausman test estimate is 38.975 and highly significant, indicating that fixed effects should be used.

Furthermore, under different types of fixed effects, the spatiotemporal double fixed effect model has the best fit and rejects degradation into time-fixed or space-fixed models. Therefore, a spatial Durbin model with double fixed effects should be selected for data fitting analysis.

3.3. Regression of the spatial Durbin model

According to the above analysis, this paper applies the spatial Durbin model with fixed effects to the three dependent variables for panel data estimation (Table 4). Due to the inclusion of lagged dependent variables in the spatial Durbin model, which violates the strict exogeneity assumption of explanatory variables in traditional regression models, the results obtained by using OLS estimation are biased and inconsistent. Therefore, this paper uses the maximum likelihood estimation (ML) method for parameter estimation.

Drawing upon the data illustrated in Table 4, the outcomes clearly reveal that enhancements in the tripartite industrial structure exert a markedly beneficial effect on GTFP, with the spatial spillover effect also yielding affirmative results. Such evidence suggests that advancements in the trio of industrial structures not only contribute to the regional escalation of GTFP but also positively affect adjacent areas.

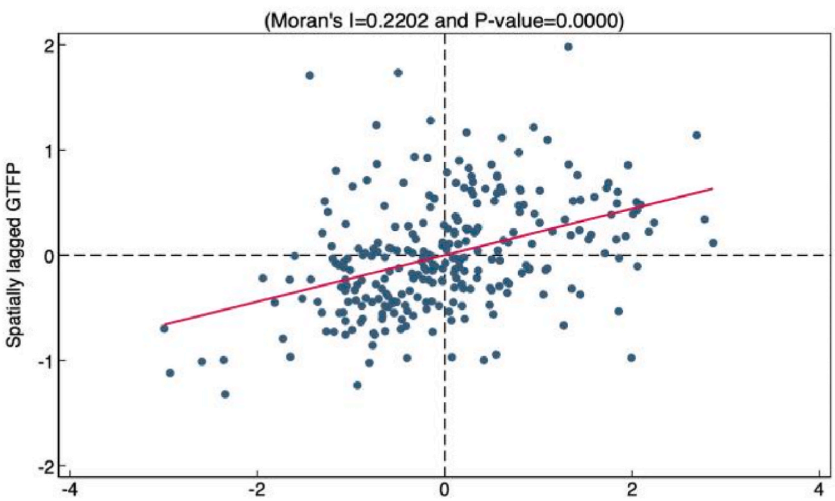

Fig. 1. Localized Moran scatter plot for GTFP in 2020.

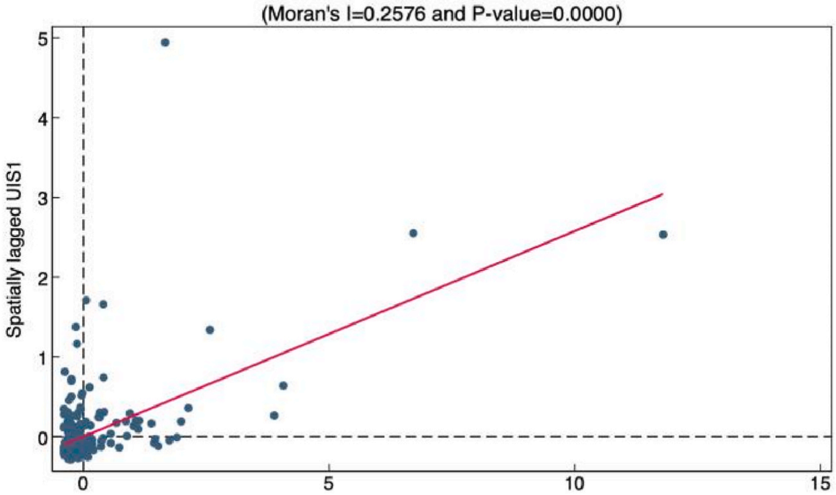

Fig. 2. Localized Moran scatter plot for UIS_1 in 2020.

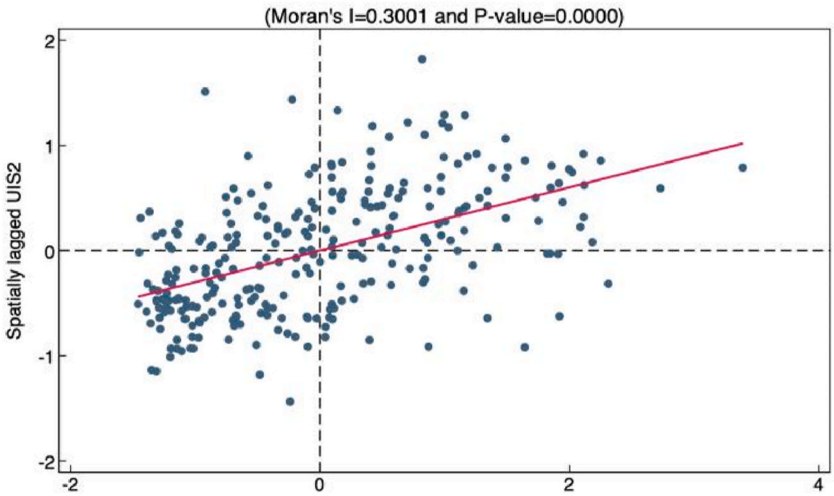

Fig. 3. Localized Moran scatter plot for UIS_2 in 2020.

Further, the impact of economic growth on GTFP varies geographically. Within the region, the better the economic development, the more it will inhibit the increase in GTFP. The reason for this may be that more developed regions will have a lower GTFP at the cost of natural resources. Conversely, economic prosperity in the region will positively affect GTFP in its neighbourhood. Advanced technology and management knowledge from more economically developed regions tends to promote GTFP in the less developed neighboring regions through different dissemination channels.In addition, economically developed regions have greater market demand and consumption capacity, which prompts the neighboring regions to improve the level of production and quality of products, which in turn promotes the development of GTFP.

Urbanisation levels have a negative impact on GTFP in both the region and neighboring regions, where the spatial effect is particularly significant. Urbanization entails the concentration of a large population in urban centers, leading to increased environmental pollution and pressures on the region as well as adjacent areas. These pollutants can be transmitted to neighboring regions through air, water, or soil, contributing to negative impacts on the local environment and ecosystem. Furthermore, neighboring regions often face challenges related to limited resource allocation, lower environmental awareness among residents, and less advanced technology compared to regions with higher levels of urbanization. Thus, their GTFP is more vulnerable to environmental factors originating from other neighboring regions.

Industrial agglomeration does not exert a substantial influence on the GTFP of the region. It is likely that this is because the region has already reached a certain threshold with regard to resource allocation and technological advancement, making industrial agglomeration ineffective in further improving production efficiency. However, neighboring regions experience a different outcome. Industrial agglomeration in these regions attracts a larger population and more enterprises, leading to resource allocation bottlenecks

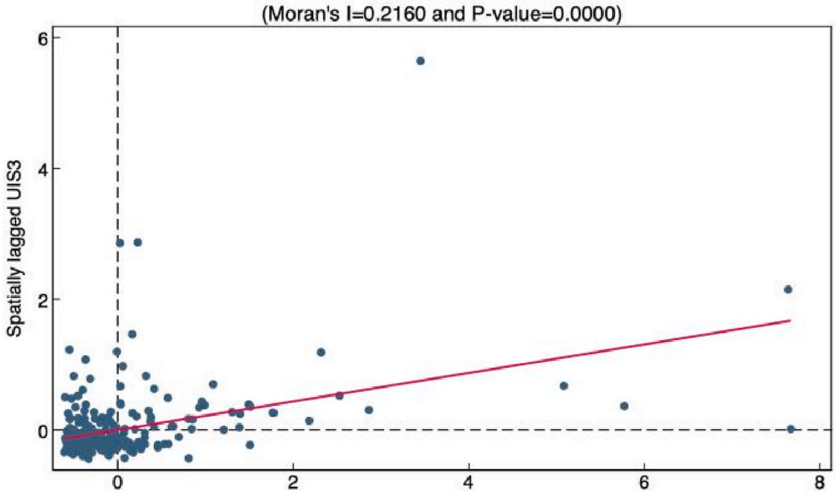

Fig. 4. Localized Moran scatter plot for UIS_3 in 2020.

Table 3
Formal tests of model settings.

Statistical quantities	Estimated value	P-value
LMlag	23.421	0.000
LMerr	21.104	0.000
RobustLMlag	23.200	0.000
RobustLMerr	22.031	0.000
Wald Spatial-lag	24.144	0.000
Wald Spatial-error	25.941	0.000
LR Spatial-lag	60.913	0.000
LR Spatial-error	60.960	0.000
Hausman	38.975	0.000
Likelihood-ratio test (Assumption: ind nested in both)	46.801	0.000
Likelihood-ratio test (Assumption: time nested in both)	32.614	0.000

Table 4
Durbin's spatial model regression.

Variables	UIS_1	UIS_2	UIS_3
	Model 1	Model 2	Model 3
lnUIS	0.689**(2.22)	0.261**(2.02)	0.277**(2.20)
lnPGDP	−0.042**(-2.56)	−0.040**(-2.41)	−0.043***(-2.63)
lnUR	−0.676**(-2.09)	−1.302**(-1.97)	−1.003**(-2.04)
lnIA	−0.050(-0.74)	−0.001(-0.01)	−0.040(-0.58)
lnFDI	2.640***(4.07)	2.708***(4.23)	2.913***(4.57)
lnGOV	1.998***(5.28)	2.010***(5.47)	2.235***(6.05)
WlnUIS	1.382**(2.10)	0.440**(2.06)	0.182*(1.83)
WlnPGDP	0.057**(2.50)	0.056**(2.41)	0.063***(2.75)
WlnUR	−5.890***(-4.92)	−7.215***(-5.27)	−6.060***(-5.02)
WlnIA	−0.619***(-3.36)	−0.674***(-3.56)	−0.524***(-2.75)
WlnFDI	−2.207(-1.46)	−1.669(-1.03)	−3.191**(-2.09)
WlnGOV	−0.950(-1.44)	−0.720(-1.05)	−0.662(-1.01)
ρ	0.009***(12.22)	0.009***(12.23)	0.009***(12.25)
Fixed time	YES	YES	YES
Space fixation	YES	YES	YES
Observations	2780	2780	2780
R-squared	0.105	0.301	0.272

Note: *,**, and *** indicate the significance level, respectively, at 10%, 5% and 1%.

and strains on environmental carrying capacity. Consequently, GTFP in neighboring areas is also affected, showing a negative correlation with respect to spatial effects.

Foreign direct investment exerts a substantial and positive influence on the region's GTFP. Foreign direct investment brings valuable resources, such as new technology, managerial expertise, and capital, which enhance the region's production efficiency and innovation capacity. Consequently, the region experiences a notable improvement in GTFP. Furthermore, foreign direct investment may additionally introduce environmentally friendly and energy-efficient production methods and technologies, further contributing to the enhancement of GTFP. However, neighboring regions lack the necessary connections and cooperation with foreign direct investment enterprises, hindering them from fully capitalizing on the technological and resource advantages associated with foreign direct investment. As a result, foreign direct investment has not had a significant impact on neighboring regions.

The extent of government intervention has a notable and positive impact on the growth of GTFP within the region. However, such intervention does not yield a significant effect on neighboring regions. The region benefits from more effective government intervention due to its distinct economic, social, and cultural environment. Moreover, the formulation and implementation of government interventions are intricate processes that necessitate the consideration of various factors. Policymakers adapt policies to suit the diverse needs and characteristics of different regions, aiming to achieve optimal outcomes. Simultaneously, government interventions typically require substantial financial, human, and technical support. These resources are more readily accessible in the region compared to neighboring regions, resulting in disparities in the degree of policy impact.

3.4. Decomposition of spatial effects

LeSage and Pace [49] noted that it is probable to result in bias when analyzing spatial spillover effects using the point estimation approach of spatial econometric models. When there is spatial correlation, a change in one region's independent variable will not only directly influence that region's dependent variable, but it will also indirectly affect surrounding areas' dependent variables. To more clearly depict the direct and indirect impacts of industrial structure on GTFP as well as the overall influence on the whole area, it is required to partition the geographic total effect. Table 5 displays the findings of this study's decomposition of the geographic total impact using the "partial differentiation" approach.

The direct and indirect effects of models 1, 2, and 3 are all significantly positive, according to the findings in Table 5, with respective direct effect coefficients of 0.652, 0.271, and 0.280 and indirect effect coefficients of 1.261, 0.451, and 0.183 for the core explanatory variables. This suggests that the enhancement and streamlining of industrial structure integration, rationalization, and advancement will not only boost local GTFP growth but also positively impact neighboring regions' GTFP. The coefficients of models 1 and 2 for the total effect are, respectively, 1.913 and significant at the 1% level, 0.722 and significant at the 5% level, and 0.463 and significant at the 5% level. This demonstrates that the growth of GTFP through optimizing and upgrading industrial structure integration is noticeably better than that of industrial structure rationalization and industrial structure advancement, both locally and among neighboring locations.

Moreover, in terms of control variables, the direct role of the level of economic development is significantly negative, while the indirect role is significantly positive. This indicates that an increase in the level of local economic development suppresses the increase in local GTFP but instead promotes the increase in GTFP in neighboring areas. Both the direct and indirect impacts of urbanization rate are significantly negative, which means that the increase in urbanization level will hinder the increase of GTFP in local and adjacent areas. The direct effect of industrial agglomeration is not significant, but it is obviously negative in both the indirection effect and the total effect, which indicates that the influence of industrial agglomeration in the surrounding areas on local GTFP is much greater than that of local industrial agglomeration, and will negatively affect local GTFP. Foreign direct investment is significantly positive in models 1, 2, and 3, but significantly negative in the indirect effect of model 3, indicating that foreign direct investment will significantly boost local GTFP but will also cause negative development of GTFP in the surrounding area by inhibiting the advancement of industrial structure. Both the direct and total effects of government intervention capacity are significantly positive, while the indirect

Table 5
Decomposition of spatial effects.

		lnUIS	lnPGDP	lnUR	lnIA	lnFDI	lnGOV
Direct effect	Model 1	0.652**	−0.044**	−0.680**	−0.037	2.566***	1.993***
		(2.06)	(-2.57)	(-2.12)	(-0.57)	(4.00)	(5.06)
	Model 2	0.271**	−0.041**	−1.380**	−0.008	2.658***	2.008***
		(2.12)	(-2.43)	(-2.01)	(-0.11)	(4.21)	(5.21)
	Model 3	0.280**	−0.044***	−1.025**	−0.037	2.865***	2.240***
		(2.22)	(-2.80)	(-2.06)	(-0.56)	(4.48)	(5.87)
Indirect effect	Model 1	1.261**	0.059***	−5.617***	−0.567***	−1.909	−0.679
		(2.07)	(2.73)	(-4.69)	(-3.24)	(-1.34)	(-1.11)
	Model 2	0.451*	0.057***	−7.102***	−0.643***	−1.489	−0.549
		(1.80)	(2.58)	(-5.07)	(-3.45)	(-0.94)	(-0.85)
	Model 3	0.183*	0.065***	−6.033***	−0.505***	−3.125**	−0.559
		(1.93)	(2.90)	(-4.72)	(-2.71)	(-1.98)	(-0.90)
Total effect	Model 1	1.913***	0.015	−6.297***	−0.604***	0.657**	1.314***
		(2.84)	(0.67)	(-4.33)	(-3.27)	(2.55)	(4.82)
	Model 2	0.722**	0.016	−8.482***	−0.651***	1.169**	1.459***
		(1.98)	(0.71)	(-4.47)	(-3.28)	(2.13)	(4.12)
	Model 3	0.463**	0.021	−7.058***	−0.542***	−0.260***	1.681***
		(2.06)	(0.85)	(-3.90)	(-2.69)	(-3.04)	(4.73)

Note: *,**, and *** indicate the significance level, respectively, at 10%, 5% and 1%.

effect is not significant, showing that government intervention capacity plays a key role in promoting the development of local GTFP.

3.5. Robustness tests

To verify the robustness of the empirical results of the spatial Durbin model, an alternative method of robustness testing of the dependent variable is used in this paper. A comprehensive index system for environmental pollution was constructed and used as a non-expected output in the calculation of the Super-Efficiency Stochastic Frontier Model (SBM), resulting in a new GTFP indicator. Robustness tests were then performed with the spatial Durbin model, and the robustness test results are shown in Table 6.

Table 6 demonstrates that the estimated coefficients of the three industrial structure upgrades on GTFP after substituting the dependent variable are consistent with the sign of the estimated spatial effect coefficients in the above table, indicating that the three industrial structure upgrades do contribute to the improvement of GTFP in the local and surrounding areas during the sample period examined in this paper. Therefore, the empirical conclusions drawn earlier are considered robust.

4. Conclusions and implications

Different from prior approaches that assess the industrial structure either in aggregate or by separating it into rationalization and advancement dimensions, this study holistically evaluates the industrial structure across these three facets. Further, it investigates the spatial spillover effect of GTFP using the spatial Durbin model. The empirical analysis has led to the subsequent conclusions.

(i) GTFP, as well as the industrial structure, exhibit spatial dependence. The results of the Moran index test indicate a significant spatial correlation for both GTFP and industrial structure. Specifically, the advanced industrial structure demonstrates stronger spatial correlation. The local Moran scatter plot reveals relatively dispersed scatter plots for industrial structure wholeness and industrial structure rationalization, indicating relatively weak spatial correlation.

(ii) Different factors have different impacts on GTFP. The macro-level empirical outcome indicates that all three types of industrial structure upgrading (integration, rationalization and advancement) have significant positive impacts on regional GTFP, while also showing significant differences. Specifically, integral industrial structure has the greatest impact on regional GTFP, followed by industrial structure rationalization and the advanced industrial structure. There is a significant negative effect of the level of economic growth on GTFP, but a significant positive effect on GTFP in the spatial dimension. The urbanization rate significantly and negatively influences GTFP in both spatial dimensions. Industrial agglomeration has a notable negative impact on GTFP only in the spatial dimension, whereas foreign investment and government intervention have remarkable positive effects on GTFP, but lack spatial spillovers.

(iii) Different factors have different ways of impacting GTFP. In terms of spatial dimension, the three types of industrial structure have an obvious positive impact on GTFP directly, indirectly, and in total. The economic development level has direct and indirect effects on GTFP but no significant effects in general. The urbanization rate has not only a direct negative impact on GTFP but also an indirect negative impact. Industrial agglomeration does not have a direct impact on GTFP. The level of foreign investment and government intervention only has a direct impact on local GTFP and does not affect nearby regions.

The following suggestions for policy are made in this article based on the aforementioned study findings.

(i) Promoting the advanced industrial structure: The advanced industrial structure has the most significant impact on GTFP. In order to achieve higher levels of GTFP, it is important for governments to incentivise green technology innovation and green energy use by businesses. Additionally, increasing investments in green industries like advanced manufacturing and environmental protection services can promote the development of the industrial structure towards high technology, low carbon, and environmental protection.

(ii) Strengthening regional synergistic development: GTFP and industrial structure are spatially dependent, and the urbanization rate negatively affects GTFP. Therefore, the government should prioritize regional synergistic development by promoting coordination between cities, towns, and rural areas. Emphasizing the development of the green economy in rural areas, building ecologically livable rural environments, and enhancing GTFP in rural areas are crucial steps.

(iii) Increasing foreign investment and government intervention: Foreign investment and government intervention have a significant positive impact on GTFP. Thus, the government should actively guide and attract foreign investment to facilitate the introduction and growth of green industries. Simultaneously, the government, as a critical player in the development of the green economy, should amplify its support and intervention in the green industry by providing tax exemptions, subsidies, technical assistance, and other measures to enhance GTFP.

In addition, this study has significant scientific value in revealing the impact of industrial structure optimization and upgrading on GTFP. It offers a fresh perspective and in-depth analysis regarding the relationship between industrial structure optimization, upgrading, and green development. However, there are some limitations to consider. Firstly, the research results are based on China-specific data. Although these results have undergone rigorous empirical testing and align with China's national conditions, regional variations may restrict the generalizability of our findings beyond China. Therefore, future studies could broaden the scope of investigation by comparing data from different countries and considering the distinctive characteristics of each region.

Table 6
Robustness tests.

Variables	UIS_1	UIS_2	UIS_3
	Model 1	Model 2	Model 3
lnUIS	0.225***(4.68)	0.037***(3.32)	0.017***(4.68)
lnPGDP	0.002(0.76)	0.002(0.73)	0.002(0.70)
lnUR	−0.298***(-3.02)	−0.274**(-2.37)	−0.221**(-2.03)
lnIA	−0.013(-1.22)	−0.013(-1.12)	−0.016(-1.47)
lnFDI	0.341***(3.37)	0.303***(2.95)	0.283***(2.79)
lnGOV	−0.008(-0.13)	0.070(1.16)	0.044(0.74)
WlnUIS	0.054***(4.52)	0.021***(4.50)	0.048***(3.40)
WlnPGDP	−0.002(-0.53)	−0.003(-0.75)	−0.002(-0.62)
WlnUR	0.487***(2.58)	0.431*(1.92)	0.491**(2.53)
WlnIA	0.084***(2.91)	0.070**(2.29)	0.078**(2.55)
WlnFDI	−0.656***(-2.78)	−0.372(-1.41)	−0.439*(-1.79)
WlnGOV	−0.687***(-6.63)	−0.730***(-6.75)	−0.722***(-6.93)
ρ	0.286***(4.34)	0.288***(4.15)	0.299***(4.51)
Fixed time	YES	YES	YES
Space fixation	YES	YES	YES
Observations	2780	2780	2780
R-squared	0.091	0.307	0.050

Note: *,**, and *** indicate the significance level, respectively, at 10%, 5% and 1%.

Ethics statement

This study did not require ethics committee review and/or approval because it did not involve human or animal participation or the collection of sensitive personal information.

Informed consent is not required for this study because this study typically uses publicly available secondary data, such as published statistics, data from public databases, etc. These data are anonymized and are fully disclosed and shared.

Data availability statement

Data will be made available on request.

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CRediT authorship contribution statement

Xinbao Tian: Writing – review & editing, Writing – original draft, Methodology. **Hongwei Zhang:** Writing – original draft, Data curation.

Declaration of competing interest

The authors declare that they do not have any known financial or personal relationships that could have influenced the results presented in this paper. There are no competing interests to declare.

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