The Driving Effect Of Technological Innovation On Green Development: Dynamic Efficiency Spatial Variation

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The driving effect of technological innovation on green development: Dynamic efficiency spatial variation

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Abstract

High-tech industry has become an important position for international competition due to its strong technological innovation capabilities. Green development of the manufacturing industry is an important measure to respond to the profound changes in the global manufacturing industry, and technological innovation is the core force to drive the green development of the manufacturing industry. However, DEA model usually employed to measure the efficiencies of the innovation and green development, the internal transmission mechanism has not been thoroughly explored. In order to open the black box, this paper utilize the high-tech industry data to measure the efficiency of technological innovation process by using network Slack Based Measure (NSBM), Global Malmquist Luenberger index model (GML) is employed to evaluate and decompose the green development efficiency of high-tech industry, and the influencing mechanism between the efficiency of technological innovation and the efficiency of green development is explored by the spatial Dubin model. The results indicate that green transformation of the manufacturing industry has an obvious spatial linkage effect. In addition, technological innovation efficiency is conducive to the green development efficiency, while economic transformation efficiency and urbanization are not conducive to the green development efficiency.

Keywords: High-tech manufacturing industry; technological innovation value chain; Green development; Internal transmission mechanism; China

1. Introduction

High-tech industries are knowledge-intensive and technology-intensive industries (Yang

and Zhu, 2021). As the most active industry of technological innovation of the economic era, high-tech industries are highly valued by governments around the world, especially developed countries. After the financial crisis, developed countries implemented the re-industrialization policy to attract the return of high-end manufacturing industries, leading to profound changes in global manufacturing (Dong et al., 2020). They have formulated and implemented relevant strategic policies to vigorously promote the development of high-tech industries and seize the manufacturing high point of future industrial competition (Duan et al., 2021). This poses new challenges to the development of China's manufacturing industry.

China's economic development has entered a new development stage, and industrial development has entered the second half of the late industrialization period. The economic development during this period was characterized by shifting economic growth rates and upgrading the industrial structure. By this time, the growth rate of the manufacturing industry has dropped significantly, facing overcapacity and imbalance between supply and demand. The original extensive growth model that relies on traditional factors has been difficult to adapt to the requirements of the new stage of economic development. In the context of the new round of industrial transformation, high-tech industries have become an important position for international economic and technological competition due to their knowledge and technology intensive (Wang et al., 2020). Compared with ordinary manufacturing industry, high-tech industry has high technology innovation efficiency.

Technological innovation efficiency levels have a direct impact on the overall efficiency of China’s industry (Liu et al., 2020). Improving the efficiency of technological innovation to promote the green development ability is an important way to meet the challenges and improve the international competitiveness. Hence, due to the characteristics of the high-tech industry, which is the new engine of manufacturing green development, the Chinese government has implemented relevant policies at the national and local government levels to promote the development of high-tech industries. The report of the 19th National Congress of the Communist Party of China clearly stated that speeding up the construction of an innovative country has created a favorable policy environment for the development of China's high-tech industries. Besides, China’s peak carbon and carbon neutral targets have strengthened the urgency of the green transformation of the manufacturing industry.

Therefore, under the guidance of development environment and policy, this paper constructs a decomposition model of spatial efficiency from the perspective of high-tech industry, analyzes the spillover effect of technological innovation, and explores the dynamic influence mechanism of technological innovation and green transformation. In order to achieve the research purpose, this paper will carry out research from the following aspects: firstly, the network model is used to explore the efficiency of technological innovation chain of high-tech industry, and the regional heterogeneity of technological innovation capacity is analyzed. From the perspective of time dynamic research, this paper analyzes the technological innovation capability in different planning periods. Secondly, for the purpose of exploring the green development status of the high-tech industry and achieve the goal of high-quality development, the decomposition model is employed to measure and decompose the green development of the high-tech industry, and the heterogeneity effect of the green development of the high-tech industry is analyzed. Finally, by constructing a spatial model, this paper explores a spatial linkage of the green development of high-tech industry and the mechanism between technological innovation efficiency and green development efficiency.

2. Literature review

Technological innovation has strong social effect and is also the key to enhance national competitiveness (Liu and Dong, 2021). Improvement of technological innovation efficiency is the vital way to improve technological innovation capabilities. With the new round of scientific and technological revolution, numerous studies have been performed to assess innovation activities, which including areas, industries, and firms. About the research method, it mainly focuses on whether to open the black box of the intermediate production process. For instance, G.Carayannis et al. (2016) utilized the data of 23 European countries and their 185 corresponding regions, and proposed a model was based on DEA to evaluate the efficiency of innovation systems. Miao et al. (2021) through constructed a two-stage SBM-DEA model to evaluate the green innovation efficiency, and the process of innovation efficiency is divided into two parts: technology development and achievement efficiency. Moreover, Tobit model is used to analyze the impact of input variable and influencing factors. The results show that technology development, achievement transformation and green innovation efficiency in each region all show a trend

of fluctuating growth, and green innovation efficiency in the eastern region has always been in a leading position. Li et al. (2017) proposed a framework based on the combination of the dynamic DEA, meta-frontier analysis theory and truncated regression model focus on the efficiency of regional high-tech industries in China. The result showed that the east area is always in the lead. Wang et al. (2020) from the industry research perspective to evaluated high-tech industrial technological innovation industries based on the two-stage network DEA. Results showed the overall technological innovation efficiency of high-tech industries were relatively low. Based on previous research and analysis, the research on technological innovation efficiency mainly focuses on technological innovation in high-tech industries and technological innovation efficiency in non-high-tech industries. At the method level, the two-stage DEA method is mainly used to measure efficiency.

Energy and environmental efficiency analysis is one of the mainstream model for measuring regional sustainable development. Therefore, green development is often measured by environmental efficiency or energy efficiency (Ouyang and Yang, 2020). Shi et al. (2021) focused on Beijing industrial system and based on waste network and eco-efficiency to analyze green transformation. Zhai and An (2021) adopted the super-efficiency DEA method to calculate the green transformation efficiency of 30 provinces of China from 2009 to 2018. From the perspective of the technological innovation process, a spatial Durbin model is further proposed to investigate the impacts of technology research and development and technology commercialization on green transformation efficiency. Luo et al. (2021) employed the dataset covers a balanced panel of 30 China's provinces over the period of 2003-2017 and utilized the super efficiency slack-based model and super efficiency epsilon-based model under meta-frontier to measure eco-efficiency. The results showed that eco-efficiency in China is at a decreasing trend overall and there exists a certain heterogeneity among different regions. Han et al. (2021) measured the eco-efficiency, and assessed how industrial upgrading influences the eco-efficiency of a certain province with provincial panel data during the period 1998-2017. Xiao et al. (2021) employed a two-stage network DEA to estimate the eco-efficiency of the resource-based cities, and the results indicated that the eco-efficiency showed a promising increase. Haider and Mishra (2021) employed the Bayesian SFA to estimate the energy efficiency of Indian iron and steel firms, and there is increasing energy efficiency gap across firms.

With the rise of a new round of technological revolution, technological innovation has received more and more attention, many scholars accepted that technological innovation could reduce energy intensity and carbon emissions without compromising global economic growth (Sun et al., 2021). Luo et al. (2021) employed bootstrap truncation regression to analyze the different impacts of innovation on eco-efficiency, results indicate that the invention patent and design patent have positive effects on China's eco-efficiency, while the effect of inward foreign direct investment on eco-efficiency is different across different regions. Liu and Dong (2021) used the data envelopment analysis game cross-efficiency model to evaluate the green economy efficiency between 2003 to 2017, the spatial econometric model was utilized to explore the relationship and the transmission mechanism between technological innovation and the green economy efficiency from the perspective of natural resources and urbanization. The result indicated that the intensive effect of technological innovation was significant and could considerably improve the green economic efficiency. Sun et al. (2021) used data from the OECD Triadic Patent Families database for 24 innovating countries between the years 1994 to 2013 to investigate the effect of technological innovation within certain countries on the energy efficiency performance of neighboring countries. The results indicated that there is a positive, significant between knowledge spillover and country-specific energy efficiency performance. Most of the existing studies have analyzed the impact of technological innovation on green development from different perspectives, such as technology spillover, R&D and patent. By analyzing the impact of technological innovation on energy efficiency, Haider and Mishra (2021) pointed out that innovative capability leads to improve energy efficiency. However, the improvement of technological innovation efficiency is conducive to reducing technological input when strengthening innovation ability, and there are relatively few studies on whether technological innovation changes have an impact on green development efficiency.

Based on the status of the manufacturing industry in the national economy, the efficiency of technological innovation and the efficiency of green development are critical to achieving sustainable development. Especially now, the achievement of China's carbon peak carbon neutral goal requires the dual efforts of technological innovation efficiency and green transformation efficiency. Existing literature has discussed the efficiency of

technological innovation and the efficiency of green transformation separately, but there are few studies on whether the improvement of technological innovation efficiency and the efficiency of green transformation can achieve a joint force mechanism. As a strategic industry, the development of high-tech industry in theory is conducive to enhancing technological innovation capabilities and driving the advancement of the industrial structure. Therefore, in order to fill the blank research in this research field, From the perspective of time dynamic efficiency and decomposition efficiency, this paper analyzes the influence mechanism of technological innovation efficiency on green transformation efficiency by building a spatial model. From the perspective of time and space, this paper analyzes the driving effect of technological innovation on green transformation.

3. Methodology

3.1 Net Slack Based Measure

The traditional DEA model is a measure of the relative efficiency of decision-making units with multiple inputs and multiple outputs. One of the shortcomings of the traditional DEA model is that it ignores intermediate products or link activities, and cannot accurately evaluate the efficiency of each stage and the overall efficiency of the decision-making unit. The technology development stage is the process of transforming innovation resources into technological output, with knowledge and technology as the main output; the latter stage transforms the output of the technological research and development stage into economic benefits. Due to the different content and purpose of the input and output situation at each stage, if only the overall efficiency is considered, the evaluation effect will be general and unscientific. Based on this, Tone and Tsutsui (2009) proposed a relaxation-based network DEA model, called Net Slack Based Measure (NSBM), which can open the black box of the traditional DEA model and deal with intermediate products or link activities.

Suppose there are n $\left(j=1,\mathrm{L},n\right)$ decision-making units, each decision-making unit contains $\mathrm{K}\left(k=1,\mathrm{L},K\right)$ stages, m_k and r_k are the input and output of the k stage, respectively. (k, h) represents the link from stage k to stage h on the set L. The input resources of DMU_j in stage k are expressed as $\left\{X_j^k \in R_+^{m_k}\right\}\left(j=1,\mathrm{L},n;\ k=1,\mathrm{L},K\right)$. The output is expressed as

$\left\{y_j^k \in R_+^{r_k}\right\}\left(j=1,\mathrm{L}\ ,n;\ k=1,\mathrm{L}\ ,K\right)$. The intermediate link from stage k to stage h is expressed as $\left\{Z_j^{(k,h)} \in R_+^{t_{(k,h)}}\right\}\left(j=1,\mathrm{L}\ ,n;\ (k,h)\in L\right)$, $t_{(k,h)}$ represents the number of items linked (k, h). The production possible set $p=\left\{\left(X^k, y^k, Z^{(k,h)}\right)\right\}$ is defined as:

$$X^k \geq \sum_{j=1}^{n} X_j^k \lambda_j^k \left(k=1,\mathrm{L}\ ,K\right), \tag{1}$$

$$y^k \leq \sum_{j=1}^{n} X_j^k \lambda_j^k \left(k=1,\mathrm{L}\ ,K\right),$$

$$Z^{(k,h)} = \sum_{j=1}^{n} Z_j^{(k,h)} \lambda_j^k \left(\forall(k,h)\right)\text{(As the output of stage } k\text{)},$$

$$Z^{(k,h)} = \sum_{j=1}^{n} Z_j^{(k,h)} \lambda_j^h \left(\forall(k,h)\right)\text{(As an input to stage } h\text{)},$$

$$\sum_{j=1}^{n} \lambda_j^k = 1\left(\forall k\right),\ \lambda_j^k \geq 0\left(\forall j,k\right)$$

Where, $\lambda^k \in R_+^n$ is the intensity vector of stage K. The above model assumes variable returns to scale, and can study the technical efficiency and scale efficiency of production units. If the constraint $\sum_{j=1}^{n} \lambda_j^k = 1\left(\forall k\right)$ is removed, the return to scale remains unchanged. $DMU_o\left(o=1,\mathrm{L}\ ,n\right)$ can be expressed as:

$$\begin{aligned} x_o^k &= X^k \lambda^k + s^{k-}\left(k=1,\mathrm{L}\ ,K\right), \\ y_o^k &= y^k \lambda^k + s^{k+}\left(k=1,\mathrm{L}\ ,K\right), \\ e\lambda^k &= 1\ \left(k=1,\mathrm{L}\ ,K\right), \\ \lambda^k &\geq 0,\ s^{k-} \geq 0,\ s^{k+} \geq 0,\ \left(\forall k\right) \end{aligned} \tag{2}$$

Where, in the equation (1), $X^k = \left(x_1^k,\mathrm{L}\ x_n^k\right) \in R^{m_k \times n}$, $y^k = \left(y_1^k,\mathrm{L}\ ,y_n^k\right) \in R^{r_k \times n}$, $s^{k-}\left(s^{k+}\right)$ is the input (output) slack vector.

For the link between two adjacent stages, there are two possible situations:

(a) "Free" link type

$$\rho_o^* = \underset{\lambda^k, s^{k-}, s^{k+}}{Min} \frac{\sum_{k=1}^{k} w^k \left[1 - \frac{1}{m^k}\left(\sum_{i=1}^{m_k} \frac{s_{io}^{k-}}{x_{io}^k}\right)\right]}{\sum_{k=1}^{k} w^k \left[1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_{ro}^{k+}}{y_{ro}^k}\right)\right]} \tag{3}$$

$$X_o^k = \sum_{j=1}^{n} \lambda_j^k x_{ij} + s_{io}^{k-}\left(i=1,2,\mathrm{K}\ ,m; k=1,2,\mathrm{K}\ ,K\right),$$

$$y_o^k = \sum_{j=1}^{n} \lambda_j^k y_{rj} - s_{ro}^{k+} \left(i = 1,2,\mathrm{K}\ ,m; k = 1,2,\mathrm{K}\ ,K \right),$$

$$z^{(k,h)} \lambda^h = z^{(k,h)} \lambda^k, \left(\forall \left(k,h \right) \right),$$

$$\lambda_j^k \geq 0,\ s_{io}^{k-} \geq 0,\ s_{ro}^{\mathrm{k}+} \geq 0, \left(\forall k \right)$$

Where, $\sum_{k=1}^{k} w^k = 1,\ w^k \geq 0 \left(\forall k \right)$, w^k is the relative weight of stage *k*. Assuming that the optimal solution of the above model is $\left(\lambda_j^{k^*},\ \mathrm{s}_{io}^{k-^*},\ \mathrm{s}_{ro}^{k+^*} \right)$, the efficiency of k-stage efficiency is expressed as:

$$\rho_k = \frac{1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_{io}^{k-^*}}{x_{io}^k} \right)}{1 + \frac{1}{r_k} \left(\sum_{ro}^{r_k} \frac{s_{ro}^{k+*}}{y_{ro}^k} \right)} \left(k = 1,2,\mathrm{K}\ ,K \right) \tag{4}$$

If and only if all sub-phases are valid, the DMU is overall valid. The invalid decision unit can be adjusted by the following formula:

$$\begin{aligned} x_o^{k^*} &\leftarrow x_o^k - s^{k-*} \left(k = 1,\mathrm{K}\ ,K \right) \\ y_o^{k*} &\leftarrow y_o^k + s^{k+*} \left(k = 1,\mathrm{K}\ ,K \right) \\ z_o^{(k,h)} &\leftarrow Z^{(k,h)} \lambda^{k*} \left(\forall \left(k,h \right) \right) \end{aligned} \tag{5}$$

3.2 Global Malmquist Luenberger

The Malmquist index model is used to evaluate the total factor productivity index (TFP), and decompose it to obtain the values of innovation efficiency and technical efficiency to further analyze internal dynamic changes (Farrell, 1957). Total factor productivity refers to the efficiency of production activities of a production unit in a certain period of time, and its essence is a comprehensive manifestation of the impact of technological progress on economic development (Fare et al., 1992). Therefore, total factor productivity is often used as an important indicator to measure the level of technological development and analyze the driving force of economic growth, as well as further analyzing its internal dynamic changes. However, the Malmquist index method does not have cyclic characteristics and cannot be compared across periods. Compared with the traditional Malmquist index model, the Global Malmquist Luenberger (GML) index model overcomes the shortcomings of the traditional model. Therefore, this paper employs the GML model

of the directional distance function: both expected output and undesired output are included in the evaluation system. Emrouznejad and Yang (2016) used GML and put the carbon dioxide as an undesired output to analyze the eco-environmental efficiency of China's manufacturing industry. Fang et al. (2021) evaluated the green total factor productivity of China's extractive industries through the GML index method and comprehensively analyzed the influencing factors. The green transformation of the manufacturing industry emphasizes that under the constraints of the ecological environment, the total factor productivity can be improved while reducing energy consumption or environmental pollution. Therefore, taking environmental factors into consideration in the evaluation system when measuring total factor productivity can more accurately reflect the state of green transformation of the manufacturing industry. Chung et al. (1997) believed that a method that can better deal with undesired output efficiency evaluation is the directional distance function. Based on this, this article uses GML to evaluate green total factor productivity of manufacturing. The basic principle is: Assuming that each decision unit contains N input items $x=(x_1,\mathrm{L}\ ,x_n)\in R_+^N$, obtains M expected outputs $y=(y_1,\mathrm{L}\ ,y_n)\in R_+^M$, J items of unexpected output $b=(b_1,\mathrm{L}\ ,b_n)\in R_+^J$. The set of production possibilities can be expressed as: $P(x)=\{(y,b)|\ x \text{ could produce } (y,b)\}$.

Suppose the directional vector is $g=(g_y,g_b)$, among them $g\in R^M\times R^J$. The directional distance function is defined as: $D(x,y,b;g_y,g_b)=\max\{\beta|(y+\beta g_y,\ b-\beta g_b)\in p(x)\}$

This function shows that while the expected output increases, the undesired output decreases in the same proportion; β is the value of the directional distance function that tries to maximize the output y and minimize the pollutant b. In this paper, the directional vector is set as $g=(y,b)$, the corresponding directional distance function is expressed as $D(x,y,b)$.

Oh (2010) defines and decomposes the GML index, the current production possibility set is: $P^t(x^t)=\{(y^t,b^t)|\ x^t \text{ can produce}(y^t,b^t)\},t=1,\mathrm{L}\ ,T$.

$\mathrm{p}^G=P^1\cup P^2\cup\mathrm{L}\ P^T$ is the global production possibility set, which means the union of

all production feasible sets in the current period.

The GML index and its decomposition form are:

$$\mathrm{GML}^{t,t+1}\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right)=\frac{1+\mathrm{D}^{\mathrm{G}}\left(x^t,y^t,b^t\right)}{1+\mathrm{D}^{\mathrm{G}}\left(x^{t+1},y^{t+1},b^{t+1}\right)}$$

$$=\frac{1+\mathrm{D}^{\mathrm{t}}\left(x^t,y^t,b^t\right)}{1+\mathrm{D}^{\mathrm{t}}\left(x^{t+1},y^{t+1},b^{t+1}\right)}\times\left[\frac{1+\mathrm{D}^{\mathrm{G}}\left(x^t,y^t,b^t\right)/1+\mathrm{D}^{\mathrm{t}}\left(x^t,y^t,b^t\right)}{1+\mathrm{D}^{\mathrm{G}}\left(x^{t+1},y^{t+1},b^{t+1}\right)/1+\mathrm{D}^{\mathrm{t+1}}\left(x^{t+1},y^{t+1},b^{t+1}\right)}\right]$$

$$=\mathrm{EC}^{t,t+1}\times\mathrm{TC}^{t,t+1} \tag{6}$$

In the formula, $D^G\left(x,y,b\right)=\max\left\{\beta\middle|\left(y+\beta y,\ b-\beta y\right)\in P^G\left(x\right)\right\}$ is the global directional distance function, the global production possibility set is $P^G\left(x\right)$. $EC^{t,t+1}$, $TC^{t,t+1}$ represent the efficiency change and technological change in the two periods, respectively. This paper further solves the four directional distance functions in the formula. Taking period t as an example, the directional distance function of the current period $D^t\left(x^t,y^t,b^t\right)$ and the global direction distance function on the current global production possibility set $D^G\left(x^t,y^t,b^t\right)$, it is obtained by the following two linear programs:

$$\begin{aligned}
&D^t\left(x^t,y^t,b^t\right)=\max\beta\\
&s.t.\ Y^t z^t\geq\left(1+\beta\right)y_k^t\\
&B^t z^t=\left(1-\beta\right)b_k^t\\
&X^t z^t\leq x_k^t\\
&z^t\geq 0
\end{aligned} \tag{7}$$

$$\begin{aligned}
&D^G\left(x^t,y^t,b^t\right)=\max\beta\\
&s.t.\ \sum_{\Gamma=1}^{T}Y^\Gamma z^\Gamma\geq\left(1+\beta\right)y_k^t\\
&\sum_{\Gamma=1}^{T}B^\Gamma z^\Gamma=\left(1-\beta\right)b_k^t\\
&\sum_{\Gamma=1}^{T}X^\Gamma z^\Gamma\leq x_k^t\\
&z^\Gamma\geq 0
\end{aligned} \tag{8}$$

The current direction distance function in t+1 period $D^{\mathrm{t+1}}\left(x^{t+1},y^{t+1},b^{t+1}\right)$ and the global direction distance function $D^G\left(x^{t+1},y^{t+1},b^{t+1}\right)$ can be obtained in the same way.

3.3 Spatial autoregression

Spatial econometrics is an emerging branch of economics, and its main research is to solve the problems of spatial interaction and spatial dependence structure in the regression

model of cross-sectional data and panel data (Yang and Lee, 2021). Compared with the traditional autoregression, the spatial autoregression makes up for the lack of the traditional panel model to describe the economic behavior to a certain extent. The spatial panel model combines the advantages of the traditional panel data model with the spatial econometric method, which not only considers the temporal and spatial characteristics but also incorporates the spatial effects into the research system, making the estimation results more effective. Common spatial panel data models include spatial lag model, spatial error model, and spatial Dubin model. Because the spatial Dubin model overcomes the common shortcomings of the spatial lag model and the spatial error model, and integrates the spatial error model into the spatial lag model, both the spatial correlation of the dependent variable and the spatial correlation of the independent variables are considered. The spatial Dubin model is expressed as:

$$\begin{aligned} &y = \rho W y + a\tau_n + X\beta + WX\gamma + \varepsilon \\ &\varepsilon : \ N\left(0, \sigma^2 I_n\right) \end{aligned} \tag{9}$$

Wy is the spatial lag of the dependent variable, WX is the spatial lag term of the independent variable. Without considering the lag term, the regression coefficient can reflect the influence of the independent variable on the dependent variable, and the spatial Dubin model can be represented by the following situation:

$$\begin{aligned} &\left(I_n - \rho W\right) y = X\beta + WX\theta + \iota_n a + \varepsilon \\ &y = \sum_{r=1}^{k} S_r\left(W\right) x_r + V\left(W\right)\iota_n a + V\left(W\right)\varepsilon \end{aligned} \tag{10}$$

Among them,

$$S_r\left(W\right) = V\left(W\right)\left(I_n\beta_r + W\theta_r\right), V\left(W\right) = \left(I_n - \rho W\right)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \mathrm{K} \tag{11}$$

The matrix is expressed as:

$$\begin{pmatrix} y_1 \\ y_2 \\ \mathrm{M} \\ y_n \end{pmatrix} = \sum_{r=1}^{k} \begin{pmatrix} S_r\left(W\right)_{11} & S_r\left(W\right)_{12} & \mathrm{K} & S_r\left(W\right)_{1n} \\ S_r\left(W\right)_{21} & S_r\left(W\right)_{22} & & \\ \mathrm{M} & & & \\ S_r\left(W\right)_{n1} & S_r\left(W\right)_{n2} & \mathrm{K} & S_r\left(W\right)_{mn} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \mathrm{M} \\ x_{nr} \end{pmatrix} + V\left(W\right)\iota_n a + V\left(W\right)\varepsilon \tag{12}$$

$$y_i = \sum_{r=1}^{k}\left[S_r\left(W\right)_{i1} x_{1r} + S_r\left(W\right)_{i2} x_{2r} + \mathrm{K} + S_r\left(W\right)_{in} x_{nr}\right] + V\left(W\right)\iota_n a + V\left(W\right)\varepsilon$$

4. Data sources

4.1 Innovation value chain

4.1.1 Technological innovation system (TIS)

Due to the availability of data, this study mainly uses high-tech industry data from 2006 to 2016 as the research sample. Some data in Tibet, Qinghai, Xinjiang, Inner Mongolia and Hainan is not available, the data of 27 provinces in China is finally used as the research object. In order to estimate the efficiency of the innovation value chain, this paper first uses the NSBM model estimation method to estimate the efficiency in segments. When selecting input-output indicators, the main consideration is whether the selected indicators could accurately reflect the problem to be studied in this paper. Therefore, according to the preliminary research of Zhang et al. (2021) and Li et al. (2021), the selection of indicators is divided into input indicators and output indicators. The investment indicators in the technological innovation stage are: R&D activity personnel converted into full-time equivalent, R&D expenditure internal expenditure, and new product development expenditure. Output indicators are valid invention patents that could measure scientific and technological achievements.

4.1.2 Economic transformation system (ETS)

The transformation of achievements in the innovation value chain refers to the process by which high-tech companies transform or transform their technological research and development achievements (i.e. patents) into new products and realize commercialization. The original intention of companies in product innovation is not to develop new products based on industrialization or commercialization. Therefore, when companies obtain the results of the technology research and development stage, they need to transform the research results or introduce the required technologies in a targeted manner to realize the digestion and absorption of the innovation results. For enterprises, if new products want to gain market favor, they need to conduct adequate market research before proposing new technical requirements. If a new product can quickly occupy the market after its launch, other companies can realize large-scale commercialization of the technology through technology purchase and cooperation. Therefore, when selecting indicators for estimating

the conversion efficiency value of results, based on the former's literature research and practical significance, the input indicators are effective invention patents, technical transformation funds, technical funds introduced, and technology digestion and absorption of funds. The output indicators are the sales revenue of new products and the export value of new products. The two-stage indicator selection for the efficiency of the innovation value chain is shown in Table 1, and the process of the innovation value chain is shown in Fig. 1.

Table 1. Innovative value chain index selection and data sources

Innovation value chain				Unit	Data sources
TIS	Investment index	Technological personnel input	R&D activity personnel	Man/year	China Science and Technology Statistical Yearbook (2007-2017)
		Funding	Internal expenditure of R&D expenses	100 Million RMB	
			New product development funding	100 Million RMB	
	Output indicators	R&D results	Valid invention patent	Item	
ETS	Investment index	R&D results	Valid invention patent	Item	China High-tech Industry Statistical Yearbook (2007-2017)
		Funding	Technical transformation funds	100 Million RMB	
			Introduction of technology funds	100 Million RMB	
			Technology digestion and absorption of funds	100 Million RMB	
	Output indicators	Commercialized income	New product sales revenue	100 Million RMB	
			New product exports	100 Million RMB	

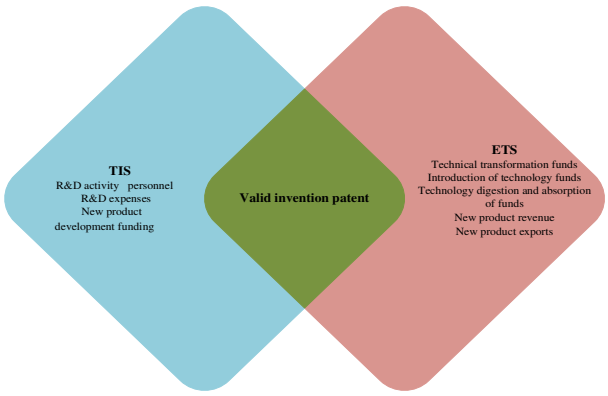

Fig.1 High-tech industry includes a multi-system series model with shared input and free intermediate output

4.2 Green total factor productivity

China's manufacturing industry is gradually changing from an extensive growth model to a scientifically intensive growth model. In the critical period of economic development transformation and governance transformation, the manufacturing industry is also at the key to transformation and upgrading. The key to the green transformation of the manufacturing industry is whether it can improve the green total factor productivity, that is, whether it can achieve a balanced development of the environment and resources while improving the quality of manufacturing production. The high-tech manufacturing industry is characterized by its high added value, high spillover, and high innovation as an important field for future international competition and an important industry that drives the transformation and upgrading of domestic industries. Improving the green total factor productivity of high-tech industries could gain an international competitive advantage in the increasingly fierce international technological competition and rising trade protectionism. Therefore, this article chooses high-tech manufacturing industry as the research object. The selection index of labor input in the input index is the average number of employees in the high-tech industry. Financial investment indicators are internal R&D expenditures and new fixed assets. The expected output indicators are mainly business income and the number of patent applications. Due to the lack of data related to the environmental pollution index of high-tech industries, Han Jing's (2012) data processing method is used for reference, and the comprehensive environmental pollution index of various places is used as an undesired output. The selection of indicators and specific data sources are shown in Table 2.

Table 2. Selection of green total factor productivity indicators and data sources for high-tech industries

		Indicator selection	Unit	Data Sources
Input indicators		Average number of employees in high-tech manufacturing	Man/Year	China Science and Technology Statistical Yearbook China High-tech Industry Statistical Yearbook China Environmental Statistics Yearbook
		Internal R&D expenditure	100 Million RMB	
		New fixed assets	100 Million RMB	
Output Indicators	Expected output	Main business income	100 Million RMB	
	Unexpected output	Number of patent applications	Item	
		Environmental pollution index		

4.3 Environment variable

4.3.1 Advanced industrial structure

Promoting the advancement of the industrial structure is an important force in the transformation and upgrading of the manufacturing industry (Zhu et al., 2019). The advanced industrial structure refers to the trend and process of continuously evolving the overall quality and efficiency of the industrial structure to a level of change through technological progress in accordance with the law of industrial structure evolution. In this paper, the indicators of advanced industrial structure are based on the indicator construction method of Fu (2010). First, take the proportion of the added value of the three industries in GDP as a sub-vector of the space vector to form a set of three-dimensional vectors $X_0 = \left(x_{1,0}, x_{2,0}, x_{3,0}\right)$. Then calculate the angle α_j between X_0 and the vector $X_1 = \left(1,0,0\right)$, $X_2 = \left(0,1,0\right)$, $X_3 = \left(0,0,1\right)$ arranged from low level to high level:

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

$$j = 1,2,3$$

The advanced industrial structure is defined as S, and the calculation formula is as follows:

$$S = \sum_{k=1}^{3} \sum_{j=1}^{k} \alpha_j \tag{14}$$

The larger the S value, the higher the level of industrial structure. The relevant data comes from the China Statistical Yearbook.

4.3.2 Outward Foreign Direct Investment

Outward foreign direct investment (OFDI), especially technology sourcing OFDI, is not only a channel for developing countries to acquire advanced technology, but also an important way and mean to overcome trade barriers from developed countries and break through the bottleneck of their own technology to enter the global high-end value chain (Zhao et al., 2020). With the rapid growth of China's economy, China's outward foreign direct investment is currently in a stage of rapid development, and its outward foreign investment ranks second in the world. Since the Chinese government actively promoted the construction of the Belt and Road in 2013, OFDI's impact on China's innovation efficiency has attracted much attention. The National Medium and Long-term Science and Technology Development Plan Outline (2006-2020) also emphasizes that innovation cannot rely solely on its own innovative strength. Therefore, exploring the impact of OFDI on the efficiency of green innovation has important practical significance. The data comes from the China Foreign Direct Investment Bulletin.

4.3.3 Informatization

With the in-depth development of networking, digitization and intelligence, informatization represents the current advanced productivity. According to the 2006-2020 National Informatization Development Strategy issued by the General Office of the Central Committee of the Communist Party of China and the General Office of the State Council, informatization refers to making full use of information technology, developing information resources, promoting information exchange and knowledge sharing, and thereby improving the quality of economic growth and promoting the transformation of economic and social development. Therefore, according to the characteristics of informatization, it can improve the efficiency of industrial resource allocation and increase

the added value of the industry in its development process, and promote the transformation and upgrading of industrial enterprises (Zhu and Sun, 2020). According to the existing literature research and the availability of data, this article uses the number of Internet users in each province to measure the degree of informatization development in each province. The data comes from the China Statistical Yearbook.

4.3.4 Control variable

GDP per capita is often used as an indicator of economic development in development economics and is one of the important macroeconomic indicators. In this article, per capita GDP is used as an indicator to measure the impact of economic development on the green transformation of manufacturing.

The Central Committee of the Communist Party of China proposed in the decision of the Third Plenary Session of the 18th Central Committee to make the market play a decisive role in the allocation of resources. In addition, in recent years, the supply-side structural reform has been further proposed to improve resource allocation and increase economic efficiency. Therefore, under the call of the government and the promotion of policies, market-oriented reform has become the most important task of China's economy at present, and it is also an important factor in improving total factor productivity. This paper attempts to explore the impact of marketization development on the green transformation of manufacturing.

Enterprise competitiveness refers to the comprehensive ability of an enterprise to realize its own value on the basis of creating value for customers through its own capabilities, and comprehensive utilization of internal resources and external resources (Tu and Wu, 2020). In this study, corporate competitiveness uses the number of companies in high-tech industries as an indicator to explore the impact of corporate competitiveness on the green transformation of manufacturing.

Since the reform and opening up, with the acceleration of industrialization, the process of urbanization has accelerated. At present, China is in a critical period of economic transformation, an important period for the modern development of socialism and a critical period for the in-depth development of urbanization. Chen et al. (2021) pointed out that urbanization has beneficially promoted the transformation and upgrading of the industrial structure and is a powerful driving force. Therefore, this paper explores the impact of the

development of urbanization on the green transformation of manufacturing. The data comes from the China Statistical Yearbook.

5. Analysis of regional heterogeneity of high-tech industry technological innovation value chain and green total factor productivity development

5.1 Analysis on the efficiency and regional heterogeneity of manufacturing technology innovation value chain

5.1.1 Analysis of the efficiency of technological innovation value chain

The innovation efficiency of high-tech industries is an important manifestation of a country or region's scientific and technological R&D strength and economic competitiveness. Improving technological innovation efficiency is the key to improving competitiveness. High-tech industry innovation process includes multi-input, multi-output, and multi-link process, which is called the technological innovation value chain according to Schumpeter's innovation theory. The technological innovation value chain includes the technological research and development stage and the economic transformation stage. Increasing R&D investment can improve R&D efficiency to a certain extent, but the presentation of high-tech achievements is in addition to investment links, but also production and product links (Zhang et al., 2019). In this paper, the research purpose is to explore the overall efficiency and segmented efficiency of the technological innovation value chain of high-tech industries, and to fully understand the technological innovation capabilities of China's high-tech industries from time and region. Therefore, this paper firstly uses the NSBM model to evaluate the technological innovation value chain and segmentation efficiency of the high-tech industry based on the relevant data of China's high-tech industry from 2006 to 2015. The technological innovation value chain of each province and its segmented efficiency results are shown in Table 3.

Table 3. Estimated value of manufacturing technology innovation value chain efficiency in each province

Region	Technological innovation value chain efficiency	Technology innovation efficiency	Economic transformation efficiency
Beijing	0.9614	0.9913	0.9517
Tianjin	0.8065	0.7022	0.9690

Hebei	0.3811	0.3338	0.5650
Shanxi	0.5277	0.6549	0.5188
Liaoning	0.5845	0.6638	0.4815
Jilin	0.5305	0.5737	0.4310
Heilongjiang	0.4257	0.4264	0.3602
Shanghai	0.6627	0.7154	0.6925
Jiangsu	0.7542	0.6659	0.8510
Zhejiang	0.6097	0.8473	0.5280
Anhui	0.2151	0.5012	0.3981
Fujian	0.6119	0.4633	0.8365
Jiangxi	0.4335	0.5753	0.4144
Shandong	0.7182	0.6853	0.6826
Henan	0.4310	0.6090	0.4696
Hubei	0.5829	0.5121	0.3826
Hunan	0.5338	0.5077	0.3847
Guangdong	0.8922	0.8838	0.8461
Guangxi	0.4229	0.4765	0.1889
Hainan	0.2800	0.2560	0.2793
Chongqing	0.7202	0.8520	0.7684
Sichuan	0.2124	0.6427	0.3277
Guizhou	0.7066	0.7805	0.7501
Yunnan	0.7661	0.7501	0.5804
Shanxi	0.5250	0.6170	0.4600
Gansu	0.4916	0.5717	0.3492
Ningxia	0.3833	0.4715	0.3151
Average	0.5619	0.6250	0.5455

Fig. 2 , Fig. 3 and Fig. 4 shows the overall efficiency of the technological innovation value chain, technological innovation efficiency and technological achievement transformation efficiency, respectively. As can be seen from the figure, regional heterogeneity exists in efficiency at different stages. And, as a whole, the efficiency of technological innovation and the innovation process is on the rise. Specifically, as shown in Table 4, during the study period, the overall efficiency of the technological innovation value chain is 0.5619, and the technological innovation efficiency and economic transformation efficiency is 0.6250 and 0.5455, respectively.

Among them, Beijing, Guangdong, Guizhou, Jiangsu, Shandong, Shanghai, Tianjin, Yunnan and Chongqing have higher than average value of technological innovation chain value efficiency, technological innovation efficiency and economic transformation efficiency. These regions belong to high innovation and high transformation. Beijing, Tianjin, Shanghai and Chongqing belong to China's four major municipalities directly

under the Central Government. Relying on government policy advantages and superior geographical location, the economy is developing rapidly, and the efficiency of technological innovation value chain, technological innovation and economic transformation efficiency are all higher than the national average. In the context of the coordinated development of Beijing-Tianjin-Hebei, the three efficiency values of Beijing area are particularly prominent, and the high-tech industries are in a state of agglomeration and development. Guangdong, Shandong, and Jiangsu are coastal cities in the eastern region, occupying favorable geographical locations and frequent foreign trade. Moreover, these provinces have developed economies, strong strengths, rapid development of high-tech industries, and relatively large R&D investment. Therefore, the efficiency value of the technological innovation value chain in these regions is higher than the national average. With the policy support of the Western Development Strategy, the overall efficiency, technological innovation efficiency and economic transformation efficiency of the technological innovation value chain in Guizhou and Yunnan are all higher than the national average.

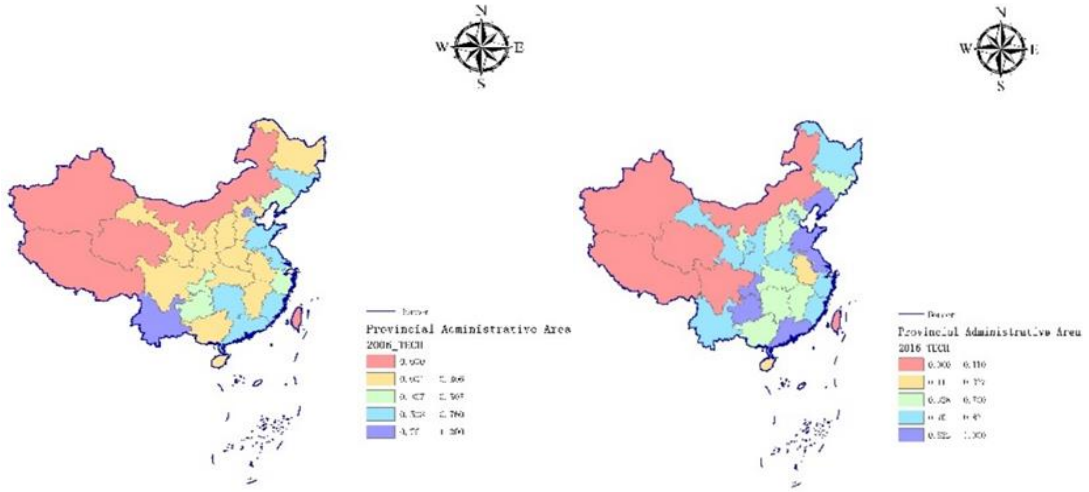

Fig. 2 Regional heterogeneity of the overall efficiency of technological innovation value chain from 2006 to 2015

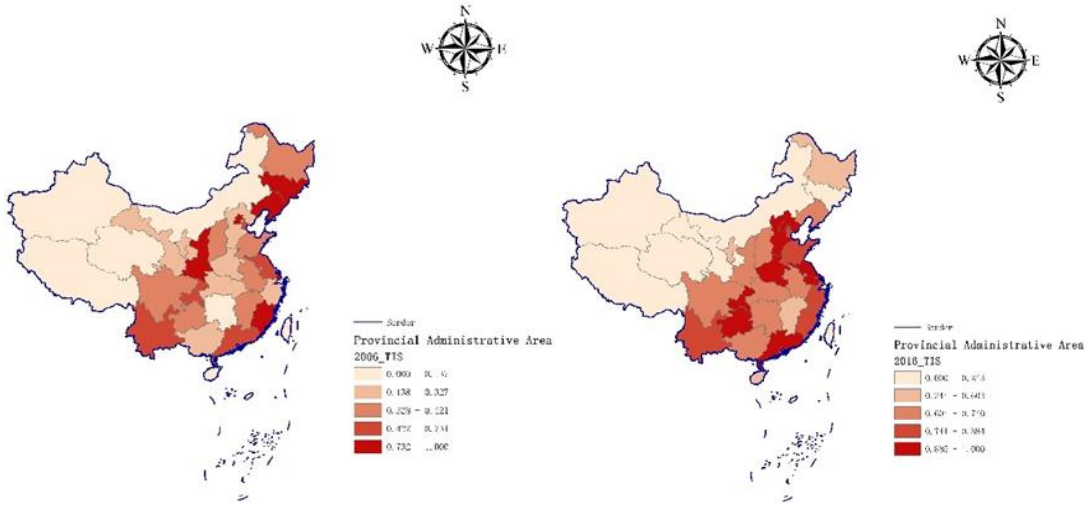

Fig. 3 Regional heterogeneity of the technological innovation efficiency from 2006 to 2015

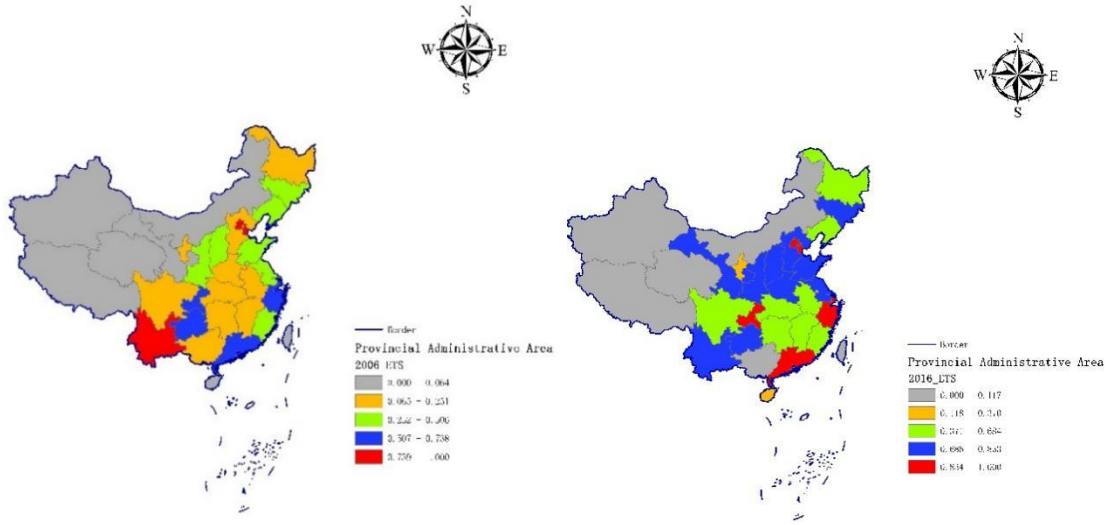

Fig. 4 Regional heterogeneity of economic transformation efficiency from 2006 to 2015

5.1.2 Analysis of regional heterogeneity of technological innovation value chain

In different periods of development, development methods and development policies will have a great impact on economic and technological development. In terms of geography, differences in geographic location and resource endowment heterogeneity will have a direct impact on industrial development and technological innovation. Therefore, this paper further analyzes the efficiency of the technological innovation chain of high-tech industries from the perspective of time and region. According to the national economic development plan, combined with the research interval, the time is divided into two stages: the 11th Five-Year Plan (FYP) period and the 12th FYP. According to the administrative

division of the People's Republic of China, the study area is divided into four major economic administrative areas, namely the eastern region, the central region, the western region and the northeast region. The efficiency of the high-tech industry technological innovation value chain at various development stages and region is shown in Table 4.

Table 4. Regional differences in the efficiency of technological innovation value chains in different development strategies

	11th FYP（2006-2010）			12th FYP（2011-2015）		
	Overall efficiency	Technological innovation efficiency	Economic transformation efficiency	Overall efficiency	Technological innovation efficiency	Economic transformation efficiency
Eastern	0.5728	0.5859	0.5696	0.7469	0.8077	0.7663
Central	0.3632	0.4022	0.2774	0.5296	0.6916	0.5536
Western	0.3963	0.4913	0.3910	0.6387	0.7347	0.5701
Northeast	0.2352	0.4942	0.2160	0.5844	0.4774	0.6018

As shown in Table 4, the overall efficiency, technological innovation efficiency, and economic conversion efficiency of the technological innovation chain of the high-tech industries in the four regions during the period of 12th FYP are all higher than that during the period of the 11th FYP. Based on the perspective of the study area, during the study period, the efficiency value of the eastern region is significantly higher than that of the central, western and northeastern regions. However, in terms of research periods, during the period of 12th FYP, the development gap between the efficiency value of the high-tech industry technological innovation value chain in the central, western and northeastern regions and the eastern region has gradually narrowed. The development focus of the eastern economic zone is the simultaneous transformation of traditional industries and existing technologies and the active improvement of the industrial structure, the transformation from traditional energy-intensive heavy industry manufacturing to knowledge and technology-intensive industries, and the active development of emerging industries. From the geographical analysis, the eastern region belongs to the coastal economic belt. The Yangtze River Delta, the Pearl River Delta and the Shandong Peninsula are all agglomerations of economic open areas, with convenient transportation, a developed commodity economy, and agglomeration of foreign-funded industries, resulting in technology spillover effects. Analyzing from the perspective of policy development strategy, the state first proposed the strategy of the eastern coastal area. Therefore,

combined with the advantages of geographical location, industrial foundation and government policy support, the eastern region has a solid economic foundation and is the most economically developed region among the four regions. With the development of economic transformation and the deepening of the industrial structure contradictions dominated by heavy industries in the Northeast, the State Council has proposed a strategy for revitalizing the Northeast and implemented a series of preferential policies for the revitalization of the Northeast. As shown by the empirical results, the efficiency of the technological innovation value chain in Northeast China during the period of 12th FYP has been improved overall compared to the period of 11th FYP. Moreover, during the 12th FYP period, the economic transformation efficiency of the Northeast region is second only to the eastern region. Under the guidance of the national development strategy, the efficiency of the technological innovation value chain, the efficiency of technological research and development, and the efficiency of economic transformation in the central and western regions during the12th FYP period have been greatly improved. During the 12th FYP period, the efficiency value of the technological innovation value chain of high-tech industries in the western region is higher than that in the central region. During the 12th FYP period, the efficiency of the technological innovation value chain and the efficiency of technological research and development in the western region are higher than those in the central region.

5.2 High-tech industry total factor productivity of green technology area Heterogeneity

5.2.1 The evolution trend of green total factor productivity in high-tech industries

High-tech industries are not only conducive to the green development of society and economy, but also an important position for international competition with their advantages of dense technology and low environmental pollution. Prioritizing the development of high-tech industries has important strategic significance for improving social and economic benefits and international competitiveness. The improvement of green total factor productivity is the key to improving the international competitiveness of high-tech industries. This paper uses the Global Malmquist Luenberger index model to measure the Green Total Factor Productivity (GTFP) of China's 27 provinces and cities in China from 2006 to 2015, and further deconstructs the technological changes (TC) and efficiency

change (EC) of the high-tech industry, the results are shown in Table 5. Fig. 5 shows the regional heterogeneity of the efficiency of green development.

Table 5. The evolution trend of manufacturing green total factor productivity

DMU	GTFP	TC	EC
Beijing	1.0913	1.0913	1.0000
Tianjin	1.0032	0.9850	1.0205
Hebei	1.0402	0.9901	1.0558
Shanxi	1.2180	1.0961	1.2063
Liaoning	1.0639	1.0246	1.0465
Jilin	1.1611	1.0530	1.2098
Heilongjiang	1.0445	0.9830	1.0770
Shanghai	1.0438	1.0438	1.0000
Jiangsu	1.0894	1.0894	1.0000
Zhejiang	1.0598	1.0451	1.1286
Anhui	1.2265	1.0383	1.2075
Fujian	1.0007	0.9892	1.0180
Jiangxi	1.1491	1.0175	1.1335
Shandong	1.1103	1.0626	1.0700
Henan	1.1478	1.0289	1.1742
Hubei	1.0665	1.0448	1.0377
Hunan	1.1142	1.0314	1.2689
Guangdong	1.0335	1.0335	1.0000
Guangxi	1.1547	1.0360	1.1344
Hainan	1.0358	1.0425	0.9950
Chongqing	1.1950	1.0455	1.1606
Sichuan	1.1757	1.0130	1.1344
Guizhou	1.0926	1.1015	1.1813
Yunnan	1.0673	1.0415	1.0507
Shanxi	1.0780	1.0635	1.0437
Gansu	1.1219	1.0785	1.2097
Ningxia	1.2304	1.0464	1.1936
Average	1.1043	1.0413	1.1021

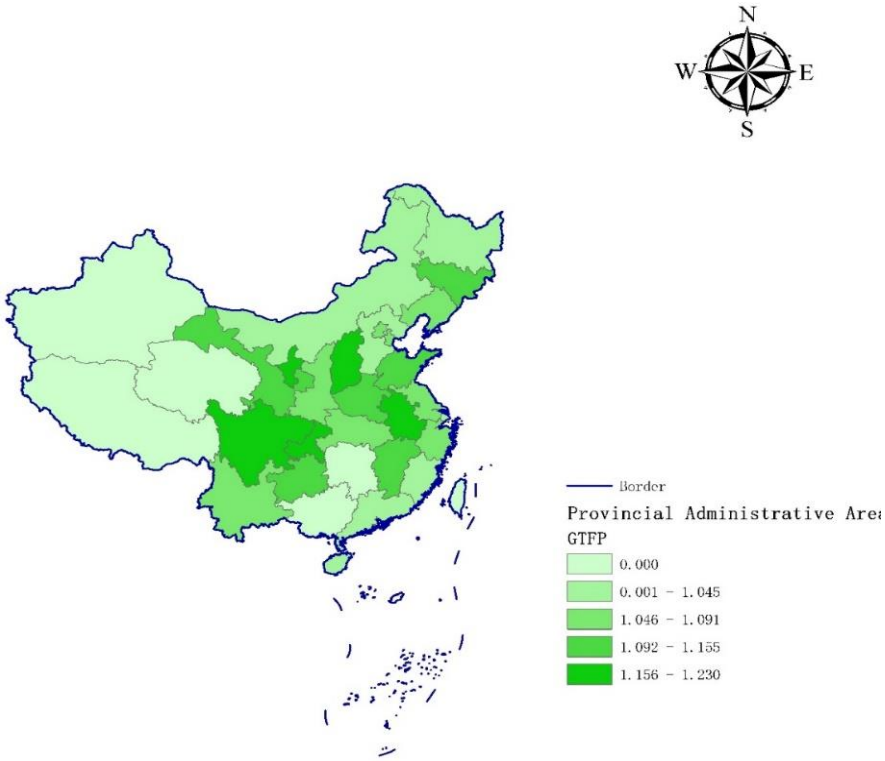

Fig. 5 Heterogeneity of green development efficiency in high-tech manufacturing industry

As shown in Table 5, the average value of the green total factor production index, technological change and efficiency change of the high-tech industry are all greater than 1, indicating that China's high-tech industry's technological innovation capabilities have been continuously improved, resources have been effectively allocated and utilized, and made considerable technological development and progress. The average production of technological changes in Tianjin, Hebei, Heilongjiang and Fujian is lower than the frontier, and the average production of Hainan Province is lower than the frontier.

5.2.2 Analysis on regional heterogeneity of green total factor productivity of high-tech industry

Due to the heterogeneity of regional development, the development of high-tech industries has become unbalanced. Based on the empirical results, this paper will analyze the development trend of green total factor productivity of high-tech industries in the four major economic regions.

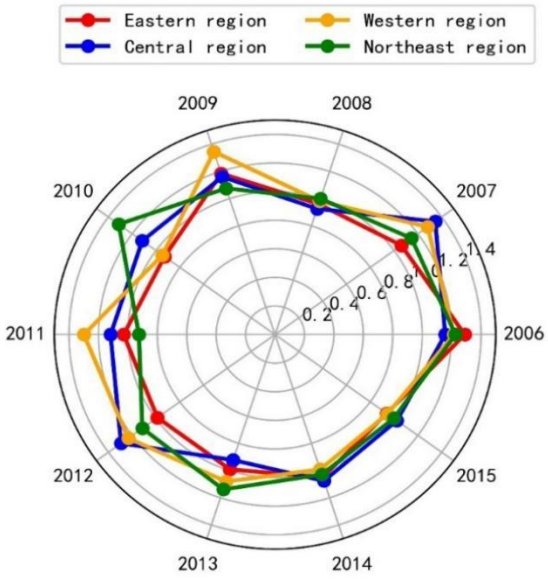

Fig. 6 The evolution trend of green total factor productivity of high-tech manufacturing industry in the central, eastern, western and northeastern

As shown in Fig.6, during the study period of 2006-2015, the green total factor productivity of high-tech industries in the eastern region developed steadily. From 2010 to 2012, the green total factor productivity was lower than the production frontier. The eastern region is dominated by coastal cities with frequent overseas trade. The global financial crisis in 2008 has impacted the economic development of China and the development of international trade. Due to the lag of technology development and transformation, the technology development and the technology spillover effect brought by foreign trade during this period were all affected, which also had an impact on the development of China's high-tech industry. The green total factor productivity, technological changes and efficiency changes of the provinces and cities in the eastern region are relatively stable, which are all higher than or at the forefront of production. The development of green total factor productivity of high-tech industries in the central, western and northeastern regions showed a fluctuating growth trend. The central provinces of Henan, Jiangxi, Shanxi and Hunan had relatively high GTFP between 2006 and 2015. With the exception of Hainan and Yunnan provinces of the western region, green total factor productivity is higher than the production frontier. With the support of the western development policy and the implementation of various preferential policies, the western region has developed rapidly, and the unbalanced regional development has gradually improved.

Table 6. Regional differences in the dynamic efficiency of high-tech manufacturing during different development strategies

	11th FYP（2006-2010）			12th FYP（2011-2015）		
	GTFP	EC	TC	GTFP	EC	TC
Eastern	1.0846	1.0281	1.0746	1.0226	1.0294	1.0061
Central	1.2224	1.2877	1.0495	1.0964	1.0373	1.0744
Western	1.1538	1.0923	1.1545	1.1275	1.1253	1.0207
Northeast	1.1522	1.0831	1.1444	1.0379	1.0833	0.9677

As shown in Table 6, during the 11th FYP period, the green total factor productivity, efficiency changes, and technological changes in the eastern region are higher than the production frontiers and are developing steadily. The green total factor productivity of the central, western and northeastern regions is all higher than the production frontier, and the green total factor productivity of the western region is the highest. During the 12th FYP period, the green total factor productivity of the eastern, central, western and northeastern regions is higher than the production frontier, and technological development has made continuous progress.

6. Analysis of spatial linkage between technological innovation and green development of high-tech manufacturing industry

6.1 Spatial model correlation test

6.1.1 Unit root test

In order to observe the data characteristics of the variables used in the research more intuitively, firstly, the variables are statistically described. The statistical results are shown in Table 7.

Table 7. Descriptive statistical characteristics of variables

Variable	Definition	Mean	Min	Max	std
gtfp	Green total factor productivity	1.0664	0.5299	1.9897	0.1846
mk	Marketization	6.6021	3.3800	10.9200	1.6350
is	Advanced industrial structure	6.5614	5.9139	7.5997	0.3123

ofdi	Outward foreign direct investment	54.5080	0.0122	909.4038	121.3200
net	Informatization	36.3338	3.7794	77.7762	17.6670
gdp	GDP per capita	39289.2357	4105.0000	164045.0000	24306.5158
eff	Technological innovation efficiency	0.625	0.006	1.000	0.2646
ce	Economic transformation efficiency	0.5433	0.0069	1.0000	0.2774
fc	Firm competition	948.1785	14.0000	6570.0000	1271.7263
ur	Urbanization	0.5349	0.2746	0.8960	0.1425

Before empirical research, it is necessary to conduct unit root tests on variables to avoid false regression and ensure the credibility of empirical results. Therefore, the unit root test in this paper adopts LLC test and IPS test respectively. The results are shown in Table 8.

Table 8. Unit Root Test

	LLC	IPS
Lngtfp	-14.9228***	-25.8273***
Lnnet	-11.1348***	-54.5154***
Lnmk	-27.7435***	-18.6759***
Lngdp	-12.5219***	-27.4218***
Lnofdi	-10.4474***	-3.7241***
Lnis	-8.0579***	-0.3461
d.lnis	-19.8573***	-8.4716***
Lneff	-42.0446***	-13.3411***
Lnce	-52.2050***	-15.4013***
Lnfc	-12.3499***	-11.2364***
Lnur	-1.1002***	-9.9410***

According to the test results, green total factor productivity (gtfp), informatization (lnnet), marketization (lnmk), GDP per capita (lngdp), outward foreign direct investment (lnofdi), technological innovation efficiency (lneff), economic transformation efficiency (lnce), firm competition (lnfc) and urbanization (lnur) have all passed the stationarity test at a confidence level of 1%, and advanced industrial structure (lnis) is a first-order

stationary sequence at a confidence level of 1%.

6.1.2 Spatial correlation test

Based on the characteristics of the spatial measurement model, before using the spatial measurement model, it is necessary to use the Moran'I index to test the spatial correlation of the research variables to determine whether the research variables have spatial correlation. According to the Moran's I index, the Moran's I index and statistical values of the green total factor productivity of China's high-tech industry from 2006 to 2015 are obtained, as shown in Table 9.

Table 9. Green Total Factor Productivity Moran's I Index of High-tech Industry

Year	Moran's I	Z
2006	0.073*	0.946
2007	0.205**	1.341
2008	0.037*	0.611
2009	0.190**	1.193
2010	0.070*	0.258
2011	0.311***	2.256
2012	0.168**	1.173
2013	0.111*	0.583
2014	0.229**	1.526
2015	0.063*	0.790

As shown in the table 9, the Moran's I value of China's high-tech industry's green total factor productivity is positive during 2006-2015 and both are significant at the level of 1%. The result indicates that green total factor productivity of China's high-tech industry will be affected by neighboring region and tend to be concentrated in space. This paper will further use Moran's I scatter plot to observe the spatial agglomeration characteristics of China's high-tech industries. The results are shown in Fig.7 and Fig.8.

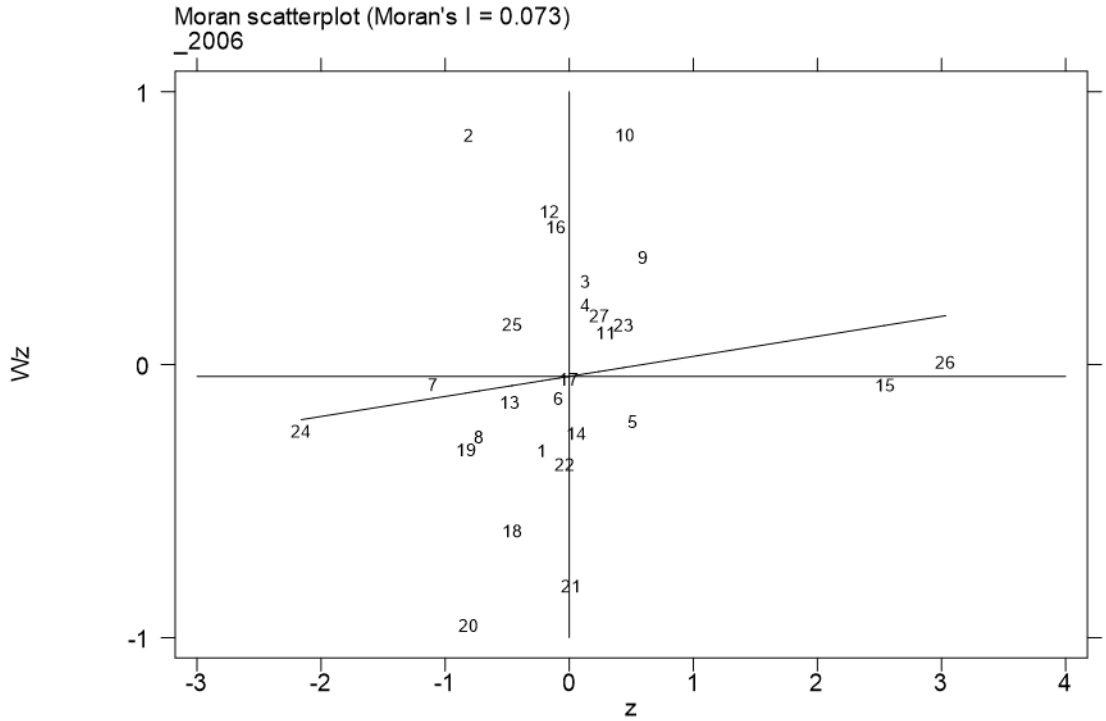

Fig. 7 Scatter plot of partial Moran's I index of green total factor productivity of high-tech industries in 2006

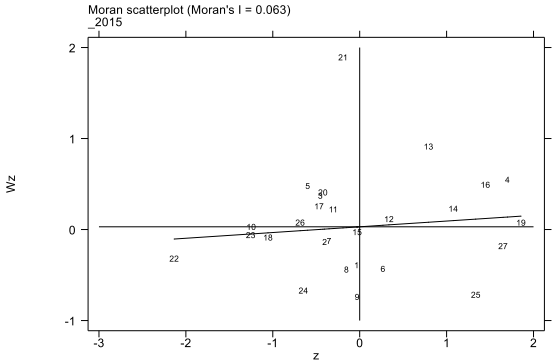

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Fig.8 Scatter plot of partial Moran's I index of green total factor productivity of high-tech industries in 2015

As shown in the figure, the partial Moran's I index of green total factor productivity in China's advanced technology industry still shows a trend of clustering. The first quadrant represents the high-high agglomeration quadrant, indicating that the green total factor productivity has a high spatial linkage effect in space. The surrounding provinces of regions with high green total factor productivity also have high green total factor productivity, which has a good diffusion effect. The third quadrant represents the low-low agglomeration quadrant, which shows the opposite development trend from the first quadrant. The green total factor productivity of the surrounding provinces in the region with low green total factor productivity is also low. The second and fourth quadrants are low-high quadrants and high-low quadrants respectively, indicating that the spatial linkage is not strong and the regional development differences are large. According to Fig. 7 and Fig. 8, it can be found that the first and third quadrants contain most of the provinces and cities, showing a high-high or low-low agglomeration feature. Therefore, the spatial measurement model is suitable for the study of this paper.

6.1.3 Spatial model selection

In the selection of the spatial model, in order to ensure the rationality of the introduction of the spatial measurement model, the LM test of the Lagranage Multiplier method and the R-LM test of its robustness are used to determine whether the spatial Dubin model (SDM) is better than the spatial error model (SEM) and the spatial lag model (SLM) is more suitable as the spatial measurement model of this research. When choosing a model, the model with a significant LM test result is preferred. If the statistical results of the two models are both significant, the comparison is made according to the robust R-LM. When the LM (lag) statistic is significant, the spatial lag model is more suitable; when the LM (err) statistic is more significant, the spatial error model is more suitable. The statistical results are shown in Table 10.

Table 10. Non-spatial panel model estimates and LR test results

Variable	Pooled OLS	Spatial Fixed	Time Fixed	Spatial & Time Fixed
Lnmk	0.0552** (0.0790)	-0.004* （0.028）	0.038*** （0020）	0.010* （0.030）

Lngdp	0.06035** (0.0294)	0.028* （0.054）	-0.003* （0.046）	0.020* （0.054）
Lneff	-0.0297*** (0.0106)	-0.126*** （0.060）	-0.052** （0.050）	-0.072** （0.058）
Lnce	0.0098** (0.0176)	0.025* （0.086）	-0.027* （0.059）	-0.004* （0.084）
Lnofdi	-0.0137** (0.0079)	-0.012** （0.013）	-0.015** （0.010）	-0.006* （0.013）
Lnfc	0.0055** (0.0110)	-0.009* （0.067）	0.009* （0.018）	0.093*** （0.072）
Lnur	-0.1318*** (0.0654)	-0.306* （0.958）	-0.114** （0.277）	-1.256*** （0.972）
Lnnet	-0.0531** (0.0348)	-0.007*** （0.003）	-0.004*** （0.002）	-0.006*** （0.003）
Lnis	-0.5887** (0.3506)	0.009* （0.197）	-0.038* （0.103）	0.068* （0.214）
_cons	0.9436** (0.8361)			
R^2	0.856	0.887	0.735	0.631
Log-L	101.598	107.472	115.668	125.425
LM(lag)	168.360***	156.951***	132.087**	29.730***
LM(err)	174.207***	90.138**	107.629***	82.360***
R-LM(lag)	89.542***	279.692**	93.923***	79.543***
R-LM(err)	77.880***	310.903***	52.524***	77.901***

After passing the LM test and the robust LM test, it is necessary to further determine whether the spatial Dubin model can be selected as the application research model in this paper. Because the spatial lag model is flexible, only considering the significance level is not rigorous enough. Therefore, this paper uses the LR test to determine whether the SDM model will degenerate into an SLM model or an SEM model. The results are shown in Table 11.

Table 11. LR test statistical results

Hypothesis	Whether SDM will degenerate into SLM	Whether SDM will degenerate into SEM
LR test	39.88	29.67
P	0.0000	0.0005

There are two null hypotheses for the LR test: the first is to test whether SDM will degenerate into SLM, and the second is whether SDM will degenerate into SEM. The statistical results of the test are shown in Table 11. The null hypotheses were rejected. Therefore, for the research of this article, the spatial Durbin model is more suitable as an application model to analyze related problems. In addition, in the choice of the model, the spatial Hausman test is needed to further test the choice of the random effect model and the fixed effect model. As shown in Table 12, according to the test results, the P value is 0.0032, and the null hypothesis is rejected at the 5% significance level. This paper chooses the fixed effects model.

Table 12. Spatial Hausman test results

Spatial Hausman Test	Chi-sq	P
	129.01	0.0032

6.2 Analysis of the spatial linkage effect between technological innovation and green transformation of manufacturing industry

Due to the close links between regional development, the green transformation of manufacturing is not only affected by the region, but also by neighboring regions. According to the test results of Moran'I index, the spatial agglomeration effect in each region is significant. Therefore, the spatial Dubin model is used to analyze the spatial linkage effect of the green transformation of high-tech industries.

Table 13. Regression estimated values of spatial Dubin model

Variables	Coe	Variables	Coe
mk	0.3544* (0.189)	W*mk	-0.3201** (0.2301)
gdp	0. 8777* (0.298)	W*gdp	0.2812 *** (0. 486)
eff	0.06376** (0.426)	W*eff	0.02327 (0.7019)
ce	-0.03560* (0.582)	W*ce	-0.033 (0.1166)
ofdi	0.1134** (0.083)	W*ofdi	0.0642* (0.2217)

fc	0.762** (0.164)	W*fc	-0.0714* (0.2215)
ur	-0.3187** (0.2142)	W*ur	-0.2071** (0.3365)
net	0.0353*** (0.015)	W*net	-0.0604* (0.2100)
is	0.3950** (0.3185)	W*is	0.6180* (0.1509)
_cons	0.7016** (1.7042)		

The regression results of the spatial Dubin model are shown in Table 13. The coefficient of local marketization is positive, indicating that the development of local marketization is conducive to the improvement of green total factor productivity in high-tech industries, and local marketization is conducive to promoting the green transformation of manufacturing. However, there is a negative relationship between the marketization of neighboring regions and the green total factor productivity of high-tech industries, indicating that the improvement of the marketization index of neighboring regions is not conducive to the green transformation of the manufacturing industry. GDP per capita could promote the improvement of green total factor productivity in high-tech industries, indicating that economic growth is conducive to promoting the green transformation of manufacturing, and the economic growth of the region will also promote the improvement of green total factor productivity in neighboring regions. There is a positive relationship between the efficiency of technological innovation and the improvement of green total factor productivity in high-tech industries, and the efficiency of technological innovation in adjacent areas also promotes the improvement of local green total factor productivity. The improvement of economic transformation efficiency and the improvement of economic transformation rate of neighboring regions are not conducive to the development of local green total factor productivity. The higher the economic transformation efficiency of the neighboring region, the higher the transformation rate of innovation achievements, the more new products will be produced, and the first to seize the market. Therefore, it is not conducive to the sales and development of local products, thereby affecting the improvement of green total factor productivity. Outward foreign direct investment in this region and neighboring regions is conducive to the improvement of green total factor productivity of high-tech industries. The results show that OFDI has a positive and positive

effect on the green total factor productivity of local high-tech industries. OFDI in neighboring areas also has a driving effect on the improvement of local green total factor productivity, but the impact is relatively small. The urbanization in this region and the urbanization in neighboring areas are not conducive to the improvement of green total factor productivity of high-tech industries. The main possible reason is the unbalanced development of urbanization. The increase in the level of firm competition and the development of informatization is conducive to the improvement of local green total factor productivity, but the development of these factors in the surrounding areas does not promote the improvement of local high-tech industry green total factor productivity. In the information age, information is currently the most advanced productive force. When the degree of local informatization is higher, the high integration of informatization and industrialization will improve local competitiveness. The advancement of the industrial structure is conducive to the improvement of local green total factor productivity, and the advancement of the adjacent region's industrial structure has an obvious driving effect on the increase of local green total factor production. In order to better analyze the relationship and spatial linkage between explanatory variables and the green total factor productivity of high-tech industries, the results of the total effect, direct effect and indirect effect are shown in Table 14.

Table 14. Direct effects and spatial linkage effects of spatial Dubin model

	Direct	Indirect	Total
mk	0.3670*** (0.2021)	-0.3397** （0.2406）	0.2708* （0.1066）
gdp	0.8028** (0.3002)	0.2437*** （0.4144）	0.1075*** （0.5380）
eff	0.0587** (0.0412)	0.0193* （0.0676）	0.0395* （0.0606）
ce	0.0360* (0.0560)	0.0085*** （0.1032）	0.0351* （0.1130）
ofdi	0.1039** (0.0822)	0.0596* （0.2039）	-0.0490 （0.2396）
fc	0.7021* (0.1630)	-0.0451 （0.0214）	0.2056 （0.1089）
ur	-0.3187** (0.2142)	-0.1843* （0.3440）	-0.5030*** （0.2158）

net	0.0305*** (0.0169)	0.0031 （0.0218）	0.0383*** （0.0185）
is	0.2403** （0.0864）	0.0695* （0.1558）	0.0719* （0.1959）

The direct effects and spatial linkage effects are shown in Table 14. The technological innovation efficiency and economic transformation efficiency of the technological innovation value chain have a positive impact on the improvement of the green total factor productivity of local high-tech industries, and the improvement of the efficiency of the technological innovation value chain in neighboring regions is also conducive to the improvement of green total factor productivity of the high-tech industries in the surrounding regions. OFDI is conducive to the improvement of green total factor productivity of high-tech industries in the region. OFDI in neighboring areas could promote the green total factor productivity of neighboring areas, but the effect is relatively small. From the results, the development of urbanization is not conducive to the improvement of green total factor productivity in the local and surrounding areas. Although the growth of China's urbanization rate has shifted from a traditional urbanization growth model to a new urbanization development model focusing on improving quality, Zheng et al. (2018) pointed out through research that, at present, China's urbanization development still has certain status of disorder development and unbalanced development. Both marketization and firm competition are conducive to the improvement of the total factor productivity of local high-tech industries, but the higher the degree of marketization in the adjacent area and the stronger the competitiveness of firms, the improvement of green total factor productivity in the surrounding areas is negatively correlated. A high degree of marketization and strong firm competitiveness are conducive to the development of local companies and the improvement of human capital, so that companies could gain advantages in market competition. The increase in per capita GDP, the high degree of informatization and the advanced industrial structure can effectively promote the growth of green total factor productivity in local high-tech industries, and the development of these factors has a radiating and leading role in the improvement of green total factor productivity in surrounding areas, which is beneficial to green transformation of manufacturing in surrounding areas.

7. Conclusion and policy recommendation

7.1 Conclusion

This paper employed the data from the 2006 to 2016 to measure the efficiency of the high-tech industry's technological innovation value chain and green total factor productivity. On this basis, it further analyzes the spatial linkage effect of the green transformation of the manufacturing industry. And draw the following main conclusions:

First, the efficiency of technological innovation in high-tech industries is higher than the efficiency of economic transformation, and the dilemma of high input and low output still exists. From a regional perspective, the efficiency of the technological innovation value chain in the eastern region is significantly higher than that in the central, western and northeastern regions. Compared with the 11th FYP period, the gap between the efficiency of the high-tech industry technology value chain in the Northeast, Central, and Western regions during the 12th FYP period and the eastern region has gradually narrowed.

Second, the Global Malmquist Luenberger index model analyzes the evolution trend and regional heterogeneity of green total factor productivity of high-tech industries. The results show that the average value of green total factor productivity, technological change, and efficiency change is greater than 1, indicating that China's high-tech industry could effectively use resources, realize the rational allocation of resources, and achieve progress and development of technological innovation capabilities. From the perspective of regional research, the green total factor productivity of high-tech industries in the eastern region developed steadily, and the development of green total factor productivity in the northeast, central and western regions showed a fluctuating growth trend. Third, according to the test results of the Moran'I index, the spatial agglomeration effect in each region is significant, indicating that the green transformation of the manufacturing industry has an obvious spatial linkage effect.

7.2 Policy recommendation

Based on the results of empirical research, this paper proposes the following policy recommendations:

First of all, establish and improve the trading platform of scientific and technological achievements, so that intellectual property rights can be implemented and the efficiency of

transformation can be improved. The empirical results show that the problems of high input and low output in high-tech industries still exist. Therefore, the relevant departments of the Chinese government should strengthen the integration of production, education and research, provide intermediary services, and improve public R&D platforms. Guide and improve relevant intellectual property laws and regulations on knowledge, patent protection, etc., and establish relevant punishment systems, and build an intellectual property legal system with Chinese characteristics based on the actual situation in China. The Chinese government departments actively promote "delegation, regulation and service" in intellectual property innovation, reduce the intervention of relevant government departments, and strengthen the role of the market in the allocation of innovation resources. Optimize core authorization procedures, standardize administrative actions in accordance with the law, appropriately shorten approval time, and improve conversion efficiency.

Second, deepen the supply-side structural reform and promote the advanced industrial structure. Based on the relevant development experience of the industrial economic development process of developed countries, the advanced industrial structure is the key to achieving economic transformation. The constraints of China's transformation from a manufacturing country to a manufacturing power are still obvious. Whether it is the external challenge of re-industrialization in developed countries or the need for high-quality development of China's internal economy, it is imperative to promote advanced manufacturing industry structure. An important way for the green transformation of manufacturing is the integrated development of information technology and manufacturing. China should continue to deepen supply-side structural reforms, further improve the level of intelligent manufacturing in manufacturing, consolidate the foundation for the integrated development of manufacturing and informatization, and promote advanced industrial structure. Construct a moderately balanced spatial layout of new urbanization, strengthen spatial governance capabilities, promote the coordinated and balanced development of informatization and marketization among regions, and build a new path to industrialization with Chinese characteristics.

Third, deepen international cooperation and promote the formation of a new pattern of full opening. In the process of advancing the high-quality development of the manufacturing industry and the advancement of the industrial structure, the innovation-

driven system is a collection of multiple innovation methods. The introduction and transformation of overseas technology will help support and deepen the integration of China's manufacturing industry and the Internet. In the international development environment where international trade protection is on the rise, China should continue to promote and deepen the development of the Belt and Road and establish mutually beneficial and friendly partnerships with countries along the route. Make good use of the unimpeded trade brought about by the Belt and Road initiative, actively promote the development of international trade and optimize the industrial chain, as well as accelerate the promotion of its position in the global value chain. Actively promote the "going out" of the entire chain of the integration of manufacturing and information technology, promote new products and services, expand overseas markets, and enhance China's international influence. Through the bringing in of foreign companies, using the resource benefits brought about by technology spillovers, understanding and learning international advanced management and business models, and promoting high-quality economic development.

Although this paper explores the impact of technological innovation on the green transformation of manufacturing from a new perspective of the technological innovation value chain, there are still areas to be improved in this paper. Although the investment in technological innovation has a positive effect on the green transformation of the manufacturing industry, whether there is a threshold for investment in technological innovation. High-tech industries are divided into six categories. Based on the heterogeneity of industry development, the current development status of high-tech industries has not been explored in detail. This will be the direction that needs to be explored in future research.

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Data availability The datasets used and analysed during the current study are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate This research did not involve human participants, human data, or human tissues. This study was based on the published materials.

Consent for Publication This research does not contain any individual person's data in the form of individual details, images, or videos. This work is based on the pubished literature.

Competing interests The authors declare no competing interests.

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