Innovation and Development Policy

Available online at http://idp-journal.casisd.cn/

Assessing the innovation efficiency of China's high–tech industry temporal–spatially: An integrated DEA approach

Su Zhang[a], Yaoyao Song[b *]

[a] School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing 100049, China
[b] School of Economics, Capital University of Economics and Business, Beijing 100070, China

Abstract

Given the significant role of the high-tech industry (HTI) in the national development, it is crucial to promote its balanced and efficient development. This study aims to investigate the innovation efficiency (IE) of the HTI of China's mainland from 2009 to 2019 and find practical paths of driving its sustained development. Using an integrated approach within the data envelopment analysis framework, we obtain both static and dynamic IE, of which we also conduct in-depth temporal and spatial analysis based on the Moran index. The results show an uneven and spatially correlated distribution of the IE, and the technological upgrading is identified as the main way of improving the efficiency. Furthermore, the Tobit regression analysis is applied to explore the impact of environmental factors on the IE from the macro perspective. The *per capita* GDP and the number of R&D institutions reveal a significantly positive effect on the improvement of the IE. Based on our main findings, we also put forward corresponding policy suggestions to enhance the competitiveness of this industry in China.

Keywords

innovation efficiency; high-tech industry; data envelopment analysis; spatial analysis

* Corresponding author. E-mail address: songyaoyao@cueb.edu.cn

10.20046/j.cnki.2096-5141.2023.0007

1. Introduction

The experience of numerous countries has confirmed the importance of innovation activities of the high-tech industry (HTI) (Hong *et al.*, 2016; Yu *et al.*, 2021). As a matter of fact, to accelerate the development of the HTI, many countries proposed policies and plans to stimulate high-tech innovations. For instance, "The Federal Big Data Research" was introduced by the United States. "The High-tech Strategy 2025" was proposed by Germany. Japan introduced the "Semiconductor Digital Industry Strategy". Similarly, the innovation activities of HTI can significantly benefit the growth of China's economy. China also launched a series of initiatives in the field of innovation, including "Made in China 2025", and "The 13th Five-year Plan on Emerging Sectors of Strategic Importance". While the HTI receives strong support from the state, it is necessary to take full advantage of various resources and promote efficiency to create more possibilities for the country.

The improvement of technology and the swift growth of the market demand help develop HTI rapidly in China (An *et al.*, 2020). As is shown in Fig. 1, with the development of HTI in China, internal expenditure on research and development (R&D) and the revenue from main business in China's HTI has maintained a continuous growth trend. Concretely, the annual average rate of growth of the revenue from the main business of the HTI was 10.29% between 2009 and 2019. The annual average rate of growth of internal expenditure on R&D was 15.60%. However, the prompt growth rate of the total scale of HTI did not synchronize with the regional innovation development status in China.

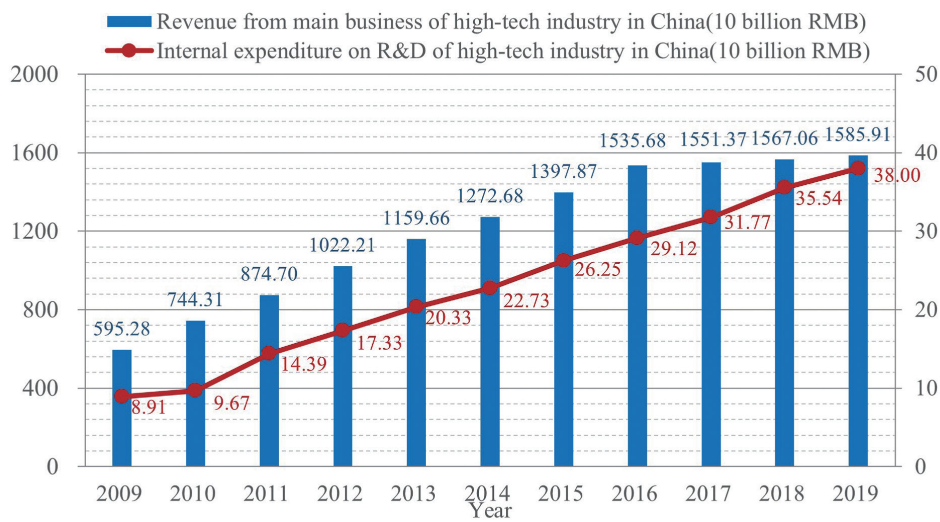


Fig. 1. Development trends of China's HTI

Previous studies have shown that China's innovation strength still lags that of several developed countries (Chen *et al.*, 2022; Chen *et al.*, 2019). Under the circumstances of the changing economic environment and limited resources, precise positioning for vulnerable regions and effective innovation efficiency (IE) improvement become the top priorities for promoting the innovation strength in China. Hence, it is necessary to conduct accurate measurement on the IE of HTI in China and identify its spatial features, so that the corresponding tactics can be made to promote the sustainable and balanced development of this industry. Besides, it also plays a significant part in clarifying the influencing factors on the IE, which is helpful for the policy-making of the HTI.

Among different efficiency measurement techniques, the data envelopment analysis (DEA) method is one of the most used approaches in measuring IE (Chiu *et al.*, 2012; Wang *et al.*, 2013; Wang and Zhang, 2018). DEA models obtained widespread applications because of their ability to deal with cases with multiple inputs and multiple outputs and the advantage of not having to preset the production function forms (Banker *et al.*, 1984; Charnes *et al.*, 1978). Nevertheless, traditional DEA models fail to take the slacks in input and output variables into consideration and make a distinction among efficient decision-making units (DMUs). The super-efficiency DEA model overcomes the difficulty of distinguishing among efficient DMUs, and the slack-based measurement (SBM) model improves the ability of DEA models to identify slack variables (Tone, 2002, 2001; Yang *et al.*, 2019). However, few studies employed the temporal and spatial analysis simultaneously to estimate the IE and explore the regional development path of the HTI in China. There is also a lack of research on the influencing factors of the IE of the HTI in China. To fill this gap, we aim to investigate the IE of the HTI in China's mainland using an integrated DEA approach. The main contributions of this article can be divided into three parts. First, it provides a research perspective that combines both static and dynamic analyses on the IE. Second, spatial analysis is conducted on the IE, and the clustering of HTI and the excessive disparity between regions in R&D intensity are discovered. Third, environmental factors that affect the IE of HTI in China are detected from a macro perspective.

The paper is structured in the following manner. Section 2 reviews and discusses the corresponding literature. In Section 3, we present our employed integrated DEA approach that combines both the super-SBM model and the Malmquist index. Section 4 describes the selected indicators and data sources and includes our empirical results and the corresponding analysis. The policy implications are proposed in Section 5. Section 6 concludes this paper.

2. Literature review

2.1. Definition and development of the HTI

Fagerberg *et al*. (1997) proposed the concept of high technology firstly, which clarifies the concept of high technology and makes it clear that the high technology is established at the frontier of modern science and technology. China issued the Notice of Statistical Classification Catalogue of the High-tech Industry in 2002 and defined the HTI as a manufacturing industry in which R&D expenditure accounts for a large proportion of the main business income. The component parts of this industry include five categories, namely manufacture of medicines, manufacture of electronic equipment and communication equipment, manufacture of computers and office equipment, manufacture of medical equipment and metres, and manufacture of electronic chemicals.

As an intelligence-intensive industry with high technology penetration, the leading technology innovation ability becomes the core competitiveness of this industry (Zhou *et al.*, 2023). As the global competition in science and technology intensifies and countries gradually increase their investment in this industry, it is gradually taking on the characteristics of high value-added, high risk, and high investment (Evenson and Westphal, 1995). For high-tech industries and enterprises, the improvement of their IE and the formation of their competitive advantages is established on the rational use of investments and resources in conducting technology introduction and independent innovation activities (Schumpeter, 2010).

The HTI started relatively late in China and was affected by the unbalanced regional economy, which led to obvious differences in the layout and development stage of the industry in different regions (Chen *et al.*, 2020). Concretely, the reserve of talents, technological and policy environment, and investment and government support for high-tech enterprises vary greatly among different regions, which all have important influences on the IE (Lin *et al*., 2012). Hence, all regions in China should identify their IE under given resources, explore practical paths to improve the IE, and formulate reasonable industrial development strategies according to their local conditions.

2.2. IE assessment in the HTI

Innovation activities have substantially improved the competitiveness of enterprises and organizations, making more and more scholars carry out research on IE evaluation in different fields, in which many performance evaluation methods have been adopted, such as the analytic hierarchy process (AHP), stochastic frontier approach (SFA), multi-criteria decision-making (Chonghui Zhang *et al*., 2022), DEA (Wang *et al*., 2023), etc. Pan *et al*. (2020) estimated the green innovation ability of manufacturing enterprises using the AHP-OVP (Osculating Value Process) model. Piao *et al*. (2022) measured the technological IE of energy companies in China during the period from 2008 to 2017 using a multiple input-output SFA model. They found that the technological IE of listed energy companies was declining. Zhong *et al*. (2021) applied a super-SBM model to measure the IE of China's regional rural commercial banks. The non-parametric Malmquist method was applied by Gurjar *et al*. (2021) to calculate the technological efficiency and the total factor productivity change index of a group of banks during the time span between 2008 and 2017. The abovementioned studies illustrate that the IE has gained extensive concern in academia.

Specifically, a group of previous research conducted the studies on IE in the HTI from both regional and industrial perspectives. In terms of the regional investigation, Guan and Chen (2010) provided systematic IE measures and conducted empirical analysis on Chinese HTI. Broekel *et al*. (2018) applied a shared input DEA approach to study the regional IE in Germany. Kalapouti *et al*. (2020) demonstrated that there were regional differences in the IE of 192 European regions. Zou *et al*. (2021) presented a super-SBM model to measure high-tech IE in China and indicated great differences within regions. In terms of the industrial investigation, the SFA and DEA methods were employed by Perelman (1995) to measure the inter-departmental innovation total-factor productivity of eight industrial sectors of OECD member countries, and the results revealed that technological progress and improvement of technical efficiency could promote the improvement of innovation total-factor productivity. Nasierowski and Arcelus (2003) measured the industrial IE of 45 countries and illustrated that IE was related to R&D resource allocation. The two-stage network DEA was adopted by Wang *et al*. (2020) in measuring IE, concluding that the overall efficiency was relatively low and that there were great differences among China's five high-tech sub-industries. Chen *et al*. (2021) applied a dynamic network SBM model to evaluate the industrial IE. These works enriched the regional and industrial studies on IE of HTI to a certain extent.

2.3. DEA-based IE investigations

Based on studies in the previous subsection, IE investigations mainly focused on the quantitative research, in which the underlying methods include parametric and non-parametric types. The parametric method is mainly based on the SFA model, whose application highly depends on the predetermination of the form of the production function. Besides, the SFA approach cannot deal with the evaluation of DMUs with multiple outputs. On the contrary, the non-parametric type is mainly founded on the DEA model. There is no need for DEA models to decide the specific form of the production function ahead of time, which effectively avoids the subjective deviation. Hence, it received widespread applications in recent years.

In the framework of DEA, the CCR model is regarded as the seminal work that was proposed on the ground of the concept of efficiency (Charnes *et al*., 1978), followed by the BCC model based on the incorporation of the variable returns to scale assumption (Banker *et al*., 1984). These traditional radial DEA models contribute greatly to studies on the IE (Carayannis *et al*., 2016; Diaz-Balteiro *et al*., 2006; He *et al*., 2021).

However, traditional radial DEA models have certain boundedness in the study of IE. On the one hand, traditional radial models only consider the proportional improvement of all inputs or outputs, without considering the possibility of non-proportional improvements (Yu *et al*., 2021). On the other hand, traditional DEA models usually generate more than one efficient DMUs, and it is difficult to distinguish between them. Therefore, kinds of advanced DEA models were proposed in recent decades, *e.g*., the SBM model and the super-efficiency model. The non-radial SBM model was established to measure the production efficiency by taking both input and output slacks into account when evaluating the efficiency of DMUs (Tone, 2001). The super-efficiency model was also put forward to distinguish the differences between efficient DMUs (Tone, 2002). To conduct the IE measurement, Piao *et al*. (2017) adopted the super-efficiency DEA to measure the IE among different kinds of companies. The SBM model was applied by Lv *et al*. (2021) to calculate the green technology IE.

Furthermore, plenty of research also conducted productivity investigations based on DEA methods. Malmquist proposed the Malmquist index to evaluate the change in the indifference curve in a consumption function (Malmquist, 1953). Färe *et al*. (1997) brought it in measuring the ratio of distance functions later and obtained broad application. The Luenberger productivity index is another important productivity index, which can accommodate the improvement of undesirable outputs (Chambers *et al*., 1996). These indices are also widely used in the performance assessment among different fields. In the field of innovation activity evaluation, the IE of listed banks was measured by Jiang and He (2018) based on the Malmquist index. Wang *et al*. (2018) applied the SBM model measuring the green total factor productivity to evaluate the green innovation activities.

In summary, to overcome the shortcomings of traditional DEA models, previous studies have used several advanced models to analyse the IE, *e.g*., the SBM model, the supper-efficiency model, and the network model. However, few studies have considered both temporal and spatial analysis on the IE, simultaneously. Hence, this paper intends to measure the regional IE of HTI in China based on the DEA approach, integrating the super-SBM model and the Malmquist index. Besides, the Moran indices and regression techniques are also used to conduct the corresponding spatial and correlation analysis.

3. Methodology

In this Section, the super-SBM model is first introduced to measure the static IE. To further conduct the dynamic analysis on the IE, we then construct the Malmquist index with its decompositions based on the static IE.

3.1. The super-SBM model

Suppose that there are a group of n DMUs being evaluated, the vectors of inputs and outputs of $DMU_j(j=1,2,...,n)$ during time $t(t=1,2,...,T)$ are defined as $x_{ij}^{t}(1,2,...m)$ and $y_{rj}^{t}(r=1,2,...q)$. Denoting the weight coefficient of DMU_j as λ_j, the production possibility set (PPS) P_t constructed from DMUs can be defined as:

$$P^t=\{(x^t, y^t)\mid x_i^t \geq \Sigma^n_{j=1}x^t_{ij}\lambda_j,\ \forall i,\ y^t_r \leq \Sigma^n_{j=1}y^t_{rj}\lambda_j,\ \forall j, \lambda_j \geq 0,\ \forall j\} \tag{1}$$

which contains all referenced DMUs to construct the benchmarking production frontier. Furthermore, we define the slacks in inputs and outputs as s_i^- and s_r^+, which are the excess input and output shortfalls of DMUs, respectively. Under the assumption of variable returns to scale (VRS), the efficiency value $\theta^t(x^t, y^t)$ can be measured by the non-oriented SBM model (Tone, 2001):

$$\theta^t(x^t, y^t)=min\frac{1-\frac{1}{m}\Sigma_{i=1}^{m}\frac{s_i^-}{x_{ik}^t}}{1+\frac{1}{s}\Sigma_{r=1}^{s}\frac{s_r^+}{y_{rk}^t}}$$
$$s.t.\Sigma_{j=1}^{n}x_{ij}^t\lambda_j+s_i^-=x_{ik}^t(\forall i)$$
$$\Sigma_{j=1}^{n}y_{rj}^t\lambda_j-s_r^+=y_{rk}^t(\forall r)$$
$$\Sigma_{j=1}^{n}\lambda_j=1$$
$$\lambda_j\geq 0(\forall j),\ s_i^-\geq 0(\forall i),\ s_i^+\geq 0(\forall r) \tag{2}$$

of which the objective function optimizes both input and output slacks and realizes the projection with both input and output improvement. Hence, the DMU_k can be considered as SBM-efficient if $s_i^-=s_r^+=0(\forall i, \forall r)$ holds. Equivalently, the DMU_k is SBM-efficient if $\theta^t(x^t, y^t)=1$. To make distinction between these efficient DMUs, Tone (2002) and Fang *et al.*(2013) further incorporated the super-efficiency idea and proposed the super-SBM model:

$$\theta^t(x^t, y^t)=min\frac{1+\frac{1}{m}\Sigma_{i=1}^{m}\frac{s_i^-}{x_{ik}^t}}{1-\frac{1}{s}\Sigma_{r=1}^{s}\frac{s_r^+}{y_{rk}^t}}$$
$$s.t.\Sigma_{j=1,j\neq k}^{n}x_{ij}^t\lambda_j-s_i^-\leq x_{ik}^t(\forall i)$$
$$\Sigma_{j=1,j\neq k}^{n}y_{rj}^t\lambda_j+s_r^+\geq y_{rk}^t(\forall r)$$
$$\Sigma_{j=1,j\neq k}^{n}\lambda_j=1$$
$$\lambda_j\geq 0(\forall j),\ s_i^-\geq 0(\forall i),\ s_r^+\geq 0(\forall r) \tag{3}$$

in which n−1 referenced DMUs other than the specific evaluated DMU_k are utilized to construct the benchmarking production technology. However, input or cost saving and output improvement are not always equally important in practical problems. For instance, some high-tech inventions can give a country a head start in the scientific and technological competition, then the cost saving becomes secondary importance. To accommodate these output-oriented application scenarios, *e.g.*, the IE evaluation of the HTI, we further modify model (3) into an output-oriented super-SBM model as follows:

$$\theta^t(x^t, y^t)=min\frac{1}{1-\frac{1}{s}\Sigma_{r=1}^{s}\frac{s_r^+}{y_{rk}^t}}$$
$$s.t.\Sigma_{j=1,j\neq k}^{n}x_{ij}^t\lambda_j-s_i^-\leq x_{ik}^t(\forall i)$$
$$\Sigma_{j=1,j\neq k}^{n}y_{rj}^t\lambda_j+s_r^+\geq y_{rk}^t(\forall r)$$
$$\lambda_j\geq 0(\forall j),\ s_i^-\geq 0(\forall i),\ s_r^+\geq 0(\forall r) \tag{4}$$

The super-SBM model allows for the efficiency value to be greater than unity. Therefore, it is conducive to the precise ranking of the IE of China's HTI.

3.2. The Malmquist index and its decompositions

The super-SBM model facilitates the static IE measurement, while the problem of incomparability of efficiency results between different periods still exist. Hence, to conduct the dynamic analysis on the IE and further explore the internal influencing mechanism within the HTI in China, we further restructure the Malmquist index (Färe *et al.*, 1997) based on the IE obtained in subsection 3.1.

Through a combination of the two adjacent periods and for the referenced and evaluated DMUs, we can measure four kinds of IE, $\theta^t(x^t, y^t)$, $\theta^t(x^{t+1}, y^{t+1})$, $\theta^{t+1}(x^{t+1}, y^{t+1})$, and $\theta^{t+1}(x^t, y^t)$. Therefore, we can restructure the Malmquist index as follows:

$$M(y^{t+1}, x^{t+1}, y^t, x^t)= \left[\frac{\theta^t(x^{t+1}, y^{t+1})}{\theta^t(x^t, y^t)} \times \frac{\theta^{t+1}(x^{t+1}, y^{t+1})}{\theta^{t+1}(x^t, y^t)} \right]^{1/2} \tag{5}$$

As a result, if , it means that the productivity has increased compared with the previous period (Song *et al.*, 2019). If , it means that the productivity remains the same as the previous period. Besides, indicates that the productivity is lower than the previous period.

Furthermore, we recombine the IE in model (5) and obtain the following decomposition of the Malmquist index:

$$M(y^{t+1}, x^{t+1}, y^t, x^t)= \frac{\theta^{t+1}(x^{t+1}, y^{t+1})}{\theta^t(x^t, y^t)} \left[\frac{\theta^t(x^{t+1}, y^{t+1})}{\theta^{t+1}(x^{t+1}, y^{t+1})} \times \frac{\theta^t(x^t, y^t)}{\theta^{t+1}(x^t, y^t)} \right]^{1/2} =EC\times TC \tag{6}$$

where the first decomposed item represents the relative change of the contemporaneous efficiency for the evaluated DMU of the two adjacent evaluation periods. In other words, it reflects the efficiency change (EC) effect. If EC is higher than unity, it indicates that the DMU has made significant progress by approaching the production frontier. The second decomposed item reflects the change of frontiers between the two periods, i.e., the technical change (TC) effect. The result of TC greater than unity indicates that organizational behaviour leads to the forward change of the production frontier by way of technological progress (Xiong *et al.*, 2018).

3.3. The Moran indexes

The Moran Index is a prevalent tool in analyzing the spatial correlation of economic variables (Fan and Myint, 2014). As a result, positive values indicate that a local improvement of the explanatory economic variable has a positive impact on the surrounding area, whereas negative values signify a negative impact accordingly. Besides, if the value of the Moran index is around zero, there is no significant spatial relationship between the variables (Liu *et al.*, 2022). When conducting spatial correlation impact analysis, attention should be paid not only to the positive or negative type of such impact, but also to the significance of such impact. In this case, the Z-score is one of the most used tools. Consequently, the significant spatial correlation (*e.g.*, at the 95% confidence level) between adjacent regions exists when the absolute value of the Z-score exceeds 1.96 (Zhang *et al.*, 2022).

3.4. The Tobit regression model

In addition to the input and output indicators within the super-SBM model that directly affect the IE, some uncontrollable external factors may also have impact on the regional innovation activities and indirectly affect the IE. There are some approaches in evaluating the impact of external factors on difference kinds of efficiency, *e.g.*, the Tobit regression model and the bootstrap regression model. In this paper, efficiency scores obtained from DEA models locate in the interval between one and unity, which means the explained variable is double censored. In addition, previous research based on the Monte Caro experiments have shown that the Tobit regression estimator performs well in a certain case (Banker and Natarajan, 2008). Therefore, the Tobit regression model is adopted in this paper to improve the accuracy and integrity of the research. The following equation is the standard Tobit model:

$$y^*_{it}=\beta X_{it}+\varepsilon_{it} \tag{7}$$

$$y_{it}=\begin{cases} y^*_{it} \ if \ y^*_{it}<0 \\ 0 \ if \ y^*_{it}\geq 0 \end{cases} \tag{8}$$

Here y^*_{it} is the latent variable, and y_{it} is the dependent variable. X_{it} is the vector of independent variables, β is the vector of correlation coefficients; and ε_{it} is the random error term and $\varepsilon_{it}\sim N(0, \sigma^2)$.

4. Empirical analysis

4.1. Variables and data sources

To conduct empirical investigation on the IE of the HTI, this study selects 28 provincial-level administrative regions in China as evaluated samples, in which Qinghai province, Xinjiang Uygur Autonomous Region, Tibet Autonomous Region, Hong Kong Special Administrative Region, Macao Special Administrative Region and Taiwan province are not included because of the unavailability of data. Following the existing research, the innovation input of the HTI is separated into human input and capital input. The full-time equivalent of R&D personnel and the internal expenditure on R&D are the core indicators of technological R&D (Aytekin *et al*., 2022), which represent the technological R&D investment carried out by universities, research institutions and R&D departments of enterprises (Liu *et al*., 2020). Therefore, the full-time equivalent of R&D personnel is used as the proxy of human input. The internal expenditure on R&D is applied as the proxy of capital input.

Moreover, based on the relevant literature, patent applications quantitatively represent industrial innovation capabilities (Chen *et al*., 2022; Cruz-Cazares *et al*., 2013). Revenue from new product sales reflects the direct economic value of new products, the stage of technology application, and commercialization carried out by core enterprises. That is, economic benefits are obtained through new product sales (Piao *et al*., 2017). Consequently, the number of patent applications and revenue from new product sales are chosen as innovation output indicators.

Concretely, information about technological invention and creation is contained in the indicator of patent applications. Market-related information is included in the revenue from new product sales. Therefore, these input and output indicators can better reflect the commercialization levels of innovation achievements. Our data are mainly collected from China Statistics Yearbook of the High Technology Industry (CSYHTI). Please see more detailed information in Table 1.

Table 1
Input and output indicators of China's HTI.

Types	Indicators	Units	Data sources
Input	The full-time equivalent of R&D personnel	Man-year	CSYHTI
	Internal expenditure on R&D	1 billion yuan	CSYHTI
Output	Revenue from new product sales	1 billion yuan	CSYHTI
	Patent applications	Piece	CSYHTI

To deal with influences of price fluctuations on revenue from new product sales and internal expenditure on R&D, two different deflators are incorporated. The indicator of the revenue from new product sales is handled by the deflator of Producer Product Index (PPI). Because of the time lag of the R&D activities, we convert the internal expenditure on R&D into the stock of internal expenditure. Before calculating the stock of internal expenditure on R&D of the HTI in each province, the indicators of the internal expenditure on R&D are handled by the deflator of a high-tech R&D Price Index. The high-tech R&D price index used here can be calculated by adding 54% of the Fixed Asset Investment Price Index and 46% of the Consumer Price Index. Some missing values are treated with linear interpolation (Zhong and Wang, 2021).

The descriptive statistics of the indicators are conducted (see Table A in the Appendix). As is shown in Table A, the differences between the maximum and minimum values of the indicators are significant. What's more, the standard deviation is greater than the mean. Considering the investment and production in HTI, we can infer that there are large gaps among the IE of HTI in the 28 provincial-level administrative regions.

4.2. Temporal analysis

4.2.1. Static analysis of the IE of the HTI in China

Based on the super-SBM model, the IE and its average value of the HTI in the 28 sample provincial-level administrative regions from 2009 to 2019 in China are shown in Table 2. It is noteworthy that the annual IE of the HTI between 2009 and 2018 is less than 0.3 among Heilongjiang, Shaanxi, and Hainan provinces. Moreover, the trend of the IE between 2009 and 2019 of Guizhou, Hebei, Shanxi, and Jilin provinces is not stable. It shows a state of cyclicality. Meanwhile, there is an obvious upward trend in the IE in Gansu, Liaoning, Hubei, Jiangxi, Chongqing, Henan, and Jiangsu provinces and Guangxi, Ningxia, and Inner Mongolia autonomous regions, while presenting a fluctuating downward trend in Tianjin municipality from 2009 to 2019. It is relatively stable with a small fluctuation range in Fujian, Hunan, Shanghai, Shandong, Sichuan, Zhejiang, and Anhui provinces, and Beijing municipality. The IE of the HTI in Yunnan decreases from 1.101 in 2009 to 0.444 in 2019. Notably, the annual IE of the HTI in Guangdong province is at the highest level.

Table 2
China's IE of the HTI in 28 provincial-level administrative regions.

DMUs	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Beijing	1.197	1.388	1.328	1.276	1.125	1.132	1.081	0.930	0.706	0.962	1.163	1.117
Tianjin	1.508	1.454	0.968	1.215	1.233	1.045	0.658	0.746	0.539	0.602	0.636	0.964
Hebei	0.265	0.281	0.244	0.326	0.270	0.314	0.264	0.329	0.291	0.463	0.824	0.352
Shanxi	0.362	0.81	0.387	0.724	0.258	0.343	0.294	0.186	0.389	0.410	0.465	0.400
Inner Mongolia	0.362	0.410	1.000	1.000	0.754	0.373	0.457	0.378	2.248	1.109	1.070	0.833
Liaoning	0.306	0.400	0.592	0.423	0.429	0.442	0.424	0.777	0.485	0.656	0.470	0.491
Jilin	0.550	0.252	0.449	0.588	0.457	0.473	0.378	0.502	0.289	0.511	0.635	0.462
Heilongjiang	0.085	0.077	0.136	0.161	0.114	0.164	0.133	0.221	0.123	0.190	0.439	0.168
Shanghai	0.795	0.726	0.710	0.593	0.511	0.630	0.607	0.602	0.529	0.719	0.803	0.657
Jiangsu	1.053	0.754	1.186	1.208	1.088	1.117	1.114	1.070	0.878	0.878	0.814	1.014

Table 2. (continued)

DMUs	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Zhejiang	0.675	0.511	0.650	0.745	1.052	0.685	0.882	0.773	0.679	0.709	0.802	0.742
Anhui	1.000	1.181	1.274	1.243	1.195	1.247	1.209	1.244	1.185	1.123	1.010	1.174
Fujian	0.657	0.676	0.633	0.657	0.574	0.494	0.593	0.675	0.509	0.614	0.722	0.618
Jiangxi	0.227	0.271	0.285	0.352	0.346	0.517	0.472	0.909	0.685	1.026	1.312	0.582
Shandong	0.722	0.738	0.721	0.697	0.640	0.627	0.793	0.756	0.704	0.720	0.635	0.705
Henan	0.406	0.377	0.366	0.360	1.382	1.432	1.298	1.338	1.237	1.371	1.088	0.969
Hubei	0.357	0.342	0.427	0.457	0.355	0.371	0.460	0.601	0.487	0.835	0.885	0.507
Hunan	0.346	0.337	1.017	0.661	0.835	0.726	0.610	0.703	0.510	0.606	0.738	0.644
Guangdong	2.204	2.836	1.898	1.882	1.958	1.835	1.829	2.015	2.433	2.652	2.736	2.207
Guangxi	0.316	0.288	0.466	0.501	0.507	0.484	0.413	0.566	0.514	1.031	1.124	0.564
Hainan	0.210	0.066	1.082	0.422	0.206	0.170	0.127	0.073	0.192	0.193	0.231	0.270
Chongqing	0.751	0.701	1.277	0.801	0.592	0.958	1.212	1.042	1.028	0.938	1.032	0.939
Sichuan	0.477	0.217	1.046	0.669	0.614	1.006	1.009	1.018	0.585	0.477	0.781	0.718
Guizhou	0.253	0.346	0.270	0.337	0.143	0.180	0.201	0.417	0.294	0.449	0.494	0.308
Yunnan	1.101	0.613	0.655	0.646	0.361	0.433	0.254	0.376	0.291	0.377	0.444	0.505
Shaanxi	0.187	0.230	0.286	0.229	0.165	0.189	0.220	0.272	0.221	0.236	0.407	0.240
Gansu	0.298	0.531	0.448	0.568	0.356	0.481	0.478	0.420	0.447	0.612	0.598	0.476
Ningxia	0.587	0.540	1.108	1.410	1.226	0.377	0.342	0.664	0.491	0.792	1.180	0.792

We further depict Fig. 2 to analyse the characteristics of the average IE. As can be observed from Fig. 2, the average score varies greatly among provincial-level administrative regions. The highest average IE of HTI is in Guangdong province. The main reason is that Guangzhou, the provincial capital of Guangdong, became one of the first state-level high-tech zones approved by the State Council in 1991. Its geographic location, economic strength, and infrastructure are conducive to the development of the HTI

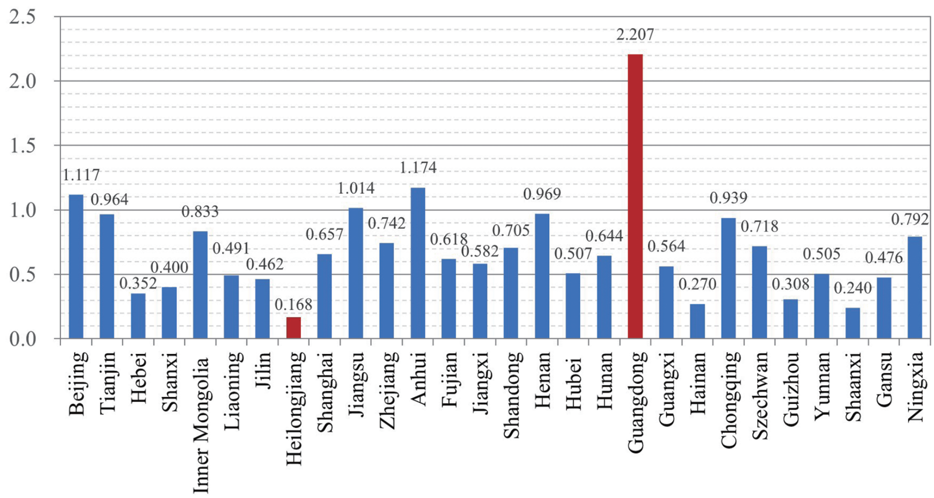


Fig. 2. The average IE of the HTI in 28 provincial-level administrative regions.

in Guangdong. The lowest average IE of HTI is in Heilongjiang province. As an industrial province, the development of innovative industries there is insufficient. Meanwhile, unfavorable geographical location and low investment in R&D lead to the lowest average IE of HTI in this province.

According to a report of the Development Research Centre of the State Council in China, China's mainland can be divided into eight economic zones geographically. The IE of the HTI in eight economic zones is shown in Table 3. Overall, the IE of HTI in China shows an increasing trend. In terms of time, from 2009 to 2019, the IE of the HTI in the middle region of the Yellow River, the middle region of the Yangtze River, the Southwest of China, the Northwest of China, and the Northeast of China all show an increasing trend. Among them, the annual average rate of growth of the IE of the HTI in the middle region of the Yellow River is 8.69%, which is the region with the highest growth rate. On the other hand, the IE of the HTI in the northern and eastern coastal regions slightly decreased. The annual average rate of growth of the IE of the HTI in the northern coastal region is -1.24%. It is lower than the annual average rate of growth of the eastern coastal region. The IE of the HTI in the southern coastal region develops stably.

Table 3
The IE of the HTI in eight major economic zones.

Regions	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
The northeast of China	0.314	0.243	0.392	0.391	0.334	0.360	0.312	0.500	0.299	0.452	0.515	0.374
The northern coast of China	0.923	0.965	0.815	0.879	0.817	0.779	0.699	0.690	0.560	0.687	0.814	0.784
The eastern coast of China	0.841	0.664	0.849	0.849	0.883	0.811	0.868	0.815	0.695	0.769	0.807	0.805
The southern coast of China	1.024	1.193	1.204	0.987	0.913	0.833	0.850	0.921	1.045	1.153	1.230	1.032
The middle region of the Yellow River in China	0.329	0.399	0.510	0.578	0.640	0.584	0.567	0.544	1.024	0.782	0.757	0.610
The middle region of theYangtze River in China	0.483	0.533	0.751	0.678	0.683	0.715	0.688	0.864	0.717	0.897	0.986	0.727
The southwest of China	0.580	0.433	0.743	0.591	0.443	0.612	0.618	0.684	0.542	0.654	0.775	0.607
The northwest of China	0.443	0.536	0.778	0.989	0.791	0.429	0.410	0.542	0.469	0.702	0.889	0.634

To compare the difference of IE more clearly among different regions, we depict a radar map of the distribution of the average IE of the HTI in eight economic zones from 2009 to 2019 in China in Fig. 3. The overall IE shows the following pattern: Southern coast > Eastern coast > Northern coast > the middle region of the Yangtze River > the Northwest of China > the middle region of the Yellow River > the Southwest of China > the Northeast of China.

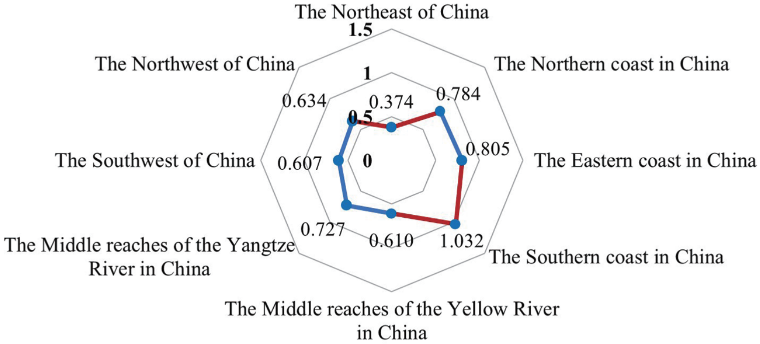


Fig. 3. The average IE of the HTI in eight economic zones.

4.2.2 Dynamic analysis of the Malmquist index of the HTI in China

To analyse the IE of the HTI from a dynamic perspective, we calculate the Malmquist index through the models in subsection 3.2. We show the results of the Malmquist index and its decomposition components in Tables B1 to B3 in the Appendix. Integrating the results, Table 4 shows the average values at different periods. The average change rate of the Malmquist index of the HTI in the 28 sample provincial-level administrative regions in China is greater than the unity for nine consecutive years. From the perspective of change trends, the Malmquist index of the HTI in China from 2009 to 2019 shows a trend of fluctuating growth, and the annual average rate of growth is 3.9%. From the decomposition results, the mean values of technical efficiency (EC) and technological progress efficiency (TC) from 2009 to 2019 also show a trend of fluctuating growth, which is consistent with the Malmquist index trend of the HTI. The annual average rate of growth of EC is 1.98%, and that of TC is 2.04%. It indicates that the improvement of the Malmquist index of the HTI innovation in China is the result of the comprehensive effect of both EC and TC. The decline in Malmquist index of the HTI in China is significant from 2017 to 2018 which is mainly because the value of TC is less than the unity. It indicates that the decline in Malmquist index in the HTI is mainly caused by TC. It further suggests that China's 28 sample provincial-level administrative regions should continue to strengthen the research and development of new technologies and products.

Table 4
The average values of the Malmquist index and decomposition results for China.

Periods	Malmquist index	EC	TC
2009-2010	0.804	1.000	0.796
2010-2011	1.892	1.963	1.157
2011-2012	1.044	1.031	1.073
2012-2013	1.187	0.947	1.291
2013-2014	1.037	1.065	0.977
2014-2015	1.084	0.975	1.119
2015-2016	1.138	1.193	0.967
2016-2017	1.298	1.107	1.241
2017-2018	1.038	1.253	0.839
2018-2019	1.132	1.194	0.955

Table 5
The average values of the Malmquist index, EC and TC in eight economic zones.

Regions	Malmquist index	EC	TC
The Northeast of China	1.149	1.166	1.033
The Northern coast in China	1.065	1.026	1.053
The Eastern coast in China	1.074	1.018	1.057
The Southern coast in China	1.403	1.502	1.097
The middle reach of the Yellow River in China	1.251	1.263	1.011
The middle reach of the Yangtze River in China	1.170	1.137	1.053
The Southwest of China	1.151	1.149	1.057
The Northwest of China	1.027	1.163	0.929

According to the classification of the eight economic zones, the average value of the Malmquist index and the average values of EC and TC from 2009 to 2019 are exhibited in Table 5. It is obvious that the average value of the Malmquist index in eight economic zones is greater than the unity. The highest average value of the Malmquist index of HTI is in the southern coast of China. The lowest of that is in the northwest of China. It indicates the uneven development in eight economic zones but the potential for breakthroughs in the evolution of high-tech industries in China. In terms of the average values of EC and TC, the average value of TC is lower than the average value of EC in the northeast of China, southern coast in China, the middle reach of the Yellow River, the middle reach of the Yangtze River, the southwest of China and the northwest of China. It shows that the abovementioned regions need to strengthen technological progress efficiency, including the research and development of new products. The average value of EC is lower than the average value of TC in the northern coast and eastern coast in China. It is mainly due to the improper innovation management and the unreasonable institutional arrangement in the HTI of these regions.

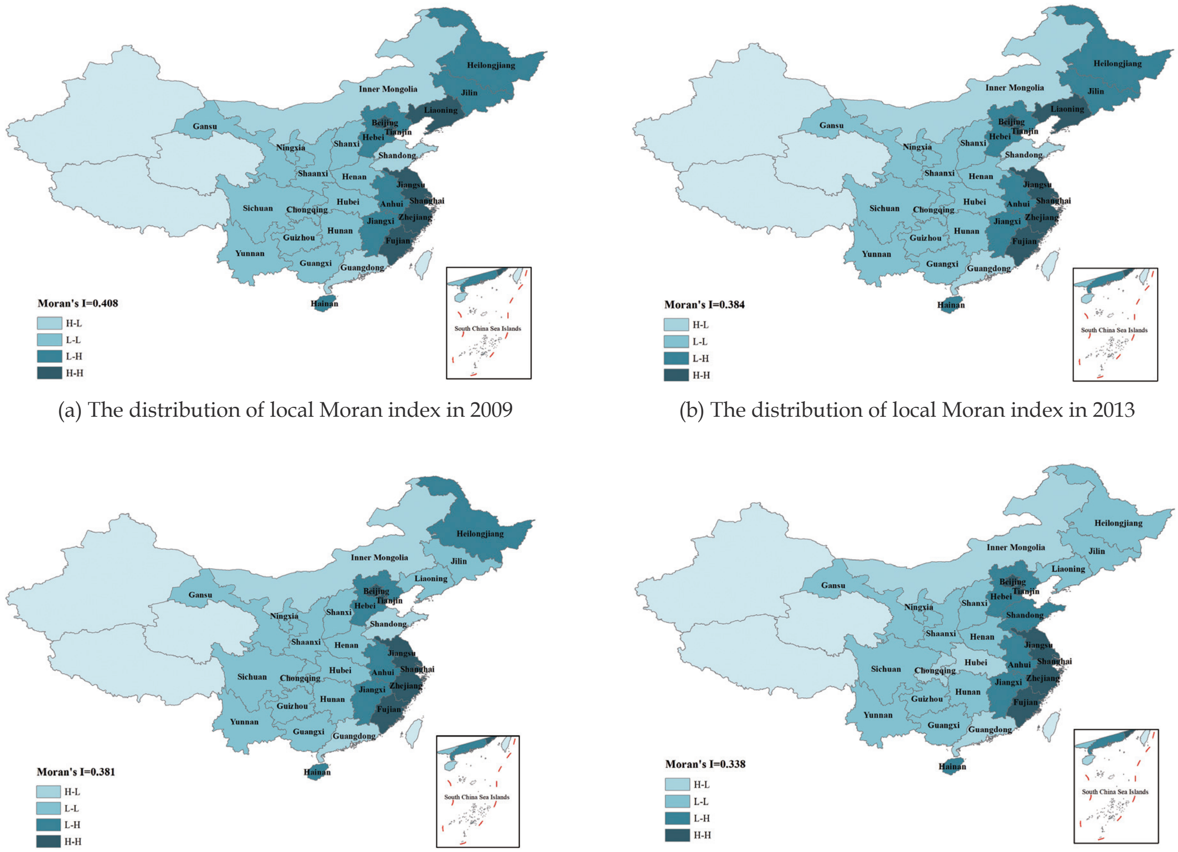
4.3. Spatial analysis

Based on the matrix calculated by ArcGIS, the global Moran index is calculated. The z value and p-value of the 28 sample provincial-level administrative regions in China are shown in Table 6. The global Moran index of the IE of the HTI in the 28 sample provincial-level administrative regions of China from 2009 to 2019 is greater than 0. Besides, the z-value is greater than the confidence interval of 1.96 (critical value = 0.05), which is statistically significant, indicating that the IE of the HTI in the 28 sample provincial-level administrative regions of China has strong spatial autocorrelation and is proportional to the spatial aggregation degree (Brown and Chung, 2006).

Table 6
The results of the global Moran index calculation.

Years	I	z	P-value*
2009	0.704	6.700	0.000
2010	0.709	6.701	0.000
2011	0.709	6.661	0.000
2012	0.711	6.669	0.000
2013	0.714	6.688	0.000
2014	0.714	6.683	0.000
2015	0.715	6.686	0.000
2016	0.706	6.636	0.000
2017	0.689	6.501	0.000
2018	0.682	6.421	0.000
2019	0.534	5.239	0.000

After determining the existence of spatial autocorrelation, the local Moran index is calculated to check out whether there is local agglomeration (see details in Fig. A in the Appendix). The distributions of the local Moran index of the HTI for 2009, 2013, 2016, and 2019 in the 28 sample provincial-level administrative regions of China are shown below.



(a) The distribution of local Moran index in 2009

(b) The distribution of local Moran index in 2013

(c) The distribution of local Moran index in 2016

(d) The distribution of local Moran index in 2019

Fig. 4. The distribution of the Moran scatter diagram of the HTI.

The Moran scatter diagram has four quadrants; the first quadrant is high-high (H-H) agglomeration, the second quadrant is low-high (L-H) agglomeration, the third quadrant is low-low (L-L) agglomeration and the fourth quadrant is high-low (H-L) agglomeration (Zhong and Wang, 2021) (see details in Figure A of Appendix). As we can see from Fig. 4, the provincial-level administrative regions located in the first quadrant are Fujian, Jiangsu and Zhejiang provinces, and Beijing, Tianjin, and Shanghai municipalities, mainly concentrated in the southern coast, northern coast, and eastern coast, which form a high-value agglomeration area for IE of the HTI. In the third quadrant, the provincial-level administrative regions are Liaoning, Jilin, Heilongjiang, Shanxi, Shaanxi, Henan, Guizhou, Yunnan, Gansu, Sichuan and Hunan provinces, and Ningxia, Guangxi, and Inner Mongolia autonomous regions, which are mainly concentrated in the northeast, the middle regions of the Yellow River, the southwest and the northwest of China. They form a low-value agglomeration area for IE of the HTI. In general, it shows that 20 provincial-level administrative regions, accounting for 71.43% of the 28 sample provincial-level administrative regions, are in the high-high (H-H) agglomeration areas or the low-low (L-L) agglomeration areas, indicating that the IE of the HTI in eight economic zones of China shows significantly positive spatial correlation distribution.

Meanwhile, the value of the local Moran index gradually decreases, from 0.408 in 2009 to 0.338 in 2019 (see Fig. 4 (a-d)), indicating that the degree of agglomeration gradually weakens with time. The main reasons include that with time, the Internet penetration rate is getting higher and higher. The HTI between different places no longer needs geographical proximity to develop. Digital technology, thus, is good news for long-distance HTI collaboration.

4.4. Analysis of influencing factors on the IE

The IE of the HTI is caused by both internal factors and external factors. There are several prevalent methods such as the Tobit regression analysis and the bootstrap procedure (Chronopoulos *et al*., 2015; Simar and Wilson, 2007). Given that the range of IE values is greater than 0 and Tobit regression analysis performed better than the bootstrap analysis statistically (Banker and Natarajan, 2008), we explore the effects of the external variables on the IE applying the Tobit regression approach.

To analyse the influence of contextual factors on IE, this study selects the external influencing factors from three aspects, including management factor, economic factor, and technological factor (Liu *et al*., 2020). The specific variables used, data sources, and calculating methods are as follows:

Management factor: As the main body, the government initiates the innovation strategy and leads the direction of innovation. The innovation of the HTI depends on government financial expenditure to a certain extent (Zou *et al*., 2021). The proportion of government expenditure in internal expenditure on R&D is used to quantify the degree of government support for the innovation of the HTI. The data supporting this variable is gathered from the CSYHTI.

Economic factor: The level of economic development is vital in the IE of HTI. The higher the level of economic development, the greater the capital investment in HTI will be, and thereby accelerating the transformation of innovation outcomes of HTI and improving the IE (Kalapouti *et al*., 2020). The *per capita* GDP is employed to represent the level of economic development. The corresponding data comes from the CSYHTI.

Technological factor: The development of the HTI cannot be separated from the R&D intensity. It is crucial to the improvement of innovation capacity. Provincial-level administrative regions with higher R&D intensity would acquire higher IE (Wang *et al*., 2020). Considering the availability of data, we select the number of R&D institutions to specifically measure the R&D intensity of high-tech sector. The relevant data is collected from the CSYHTI.

The specific environmental factors of the HTI in China are shown in Table 7 (*Per capita* GDP is handled by a GDP deflator). The descriptive statistics are exhibited in Table 8.

Table 7
Environmental factors of IE in China's HTI.

Environmental factors	Quantitative indicators	Units	Data Sources
Management factor	The proportion of government expenditure in internal expenditure on R&D	%	CSYHTI
Economic factor	Per capita GDP	Yuan-man	CSYHTI
Technological factor	Number of R&D institutions	piece	CSYHTI

Table 8
Descriptive statistics of environmental factors.

Variables	Observations	Max	Min	Mean	Median	Std. Dev
The proportion of government expenditure in internal expenditure on R&D	308	0.401	0.019	0.126	0.970	0.098
Per capita GDP	308	11.705	9.303	10.538	10.485	0.461
Number of R&D institutions of the HTI	308	8.832	2.197	4.901	4.883	1.354

Based on the analysis, we apply the Tobit regression analysis using IE as the dependent variable and three environmental variables as independent variables. The specific results are shown in Table 9.

Table 9
The Tobit regression results.

Independent variables	Coefficients	St. Err	t	P>|t|
The proportion of government expenditure in internal expenditure on R&D	-1.265***	0.228	-5.56	0.000
Per capita GDP	0.097*	0.054	1.81	0.071
Number of R&D institutions of the HTI	0.131***	0.018	7.18	0.000
Intercept	-0.818	0.540	-1.52	0.131

*Note: The symbol *** means significance at the 1% level, ** means significance at the 5% level, * means significance at the 10% level.*

We can see that the IE is statistically influenced by the abovementioned three environmental variables. The detailed explanations are as follows.

Firstly, the proportion of government expenditure in internal expenditure on R&D shows a significantly negative correlation with the IE. It is mainly because the allocated government R&D expenditure cannot be directly transformed into the innovation ability of the HTI. At the same time, most of the 28 sample provincial-level administrative regions are inland places, which are not attractive enough to young talents based on China's current national conditions. This exacerbates the phenomenon of brain drain. Hence, R&D funds allocated by the government cannot bring about further development of the regional HTI with the lack of regional scientific research talents.

Secondly, the coefficient of the *per capita* GDP is positive in the significance test at the level of 10%, *i.e.* the *per capita* GDP has significantly positive impact on the IE of the HTI in China. This is easy to explain: The increase of *per capita* GDP signifies the improvement of the regional economic development, which leads to a better environment for the regional innovation and entrepreneurship actives, infrastructure construction, talent inflow, *etc.* Hence, it brings about the improvement of regional IE of the HTI.

Thirdly, there is also a significantly positive correlation between the number of R&D institutions of the HTI and the provincial IE. It is well known that R&D institutions are specialized in scientific research and technological innovation activities, where the staffing, office environment and management system are conducive to innovation activities. Understandably, the more R&D institutions in the region, the higher the regional IE of the HTI.

5. Conclusions, implications, and limitations

5.1. Conclusions

Benefiting from the HTI, the Chinese economy achieved rapid development. However, with the fast-growing scale of HTI, problems associated with the unbalanced regional development of the industry have become increasingly prominent. These phenomena include the gathering of high-tech enterprises in the east, the excessive disparity between regions in R&D activities, and the obvious differences in the structure of regional talents. Excessive regional disparities in the development of HTI and the over-concentration of relevant resources in developed provincial-level administrative regions will hinder the spillover effect of technology, which will be detrimental to the development of a national collaborative innovation system. In general, a correct understanding of the issue of regional development differences in HTI is not only the basis for the formulation of high-tech industrial policies but also provides a certain reference for the implementation of national innovation-driven strategies. Therefore, evaluating the regional IE of the HTI and identifying the causes of the discrepancy are the primary purposes of this study.

To measure the regional IE of the HTI and identify the causes of the discrepancy, we conduct static and dynamic analysis for the HTI. We calculate the regional IE of the HTI in China from both static and dynamic perspectives and analyse the spatial distribution of the IE of the HTI in eight economic zones. The influencing factors on the IE are also explored using the Tobit regression analysis. Empirical results show that the regional development of the IE of the HTI is uneven. Strengthening technological innovation is crucial to improve the IE of HTI in the future. Additionally, the IE of the HTI in eight economic zones shows significantly positive and spatially correlated distribution characteristics, while the spatial agglomeration gradually weakens with time. Moreover, the *per capita* GDP and the number of R&D institutions have a significantly positive correlation with the improvement of the IE of the HTI in China, while the proportion of government expenditure in internal expenditure on R&D has a significantly negative effect on it. Overall, this study analyses the regional IE of the HTI in China from both static and dynamic perspectives. Subsequently, the results find practical paths to improving the regional development of the IE of the HTI.

In view of the empirical analysis, the results should be exhibited for making relevant suggestions. Firstly, given the uneven development state of the regional high-tech sector, regional governments are supposed to implement targeted measures to promote coordinated regional development of the HTI. Secondly, the fluctuation of the Malmquist index is mainly caused by TC from 2009 to 2019, and TC symbolizes the capacity of technological innovation in the HTI. Thus, the HTI should adhere to innovation in technology. Thirdly, based on the investigations on external influencing factors on IE, we find that the proportion of government expenditure in internal expenditure on R&D has a significantly negative correlation with the IE while the effects on IE of *per capita* GDP and the number of R&D institutions are opposite.

5.2. Policy suggestions and limitations

Based on the results, we bring forward the following policy suggestions.

Firstly, it’s necessary for policymakers to establish and improve the high-level inter-regional collaborative innovation system for the HTI. The IE of the HTI on the southern coast is the highest, while the IE of the HTI in the northeast of China is the lowest. Differences in the IE in the regional HTI are significant. The regions in the northeast, the northwest, and the southwest should not only focus on the use of innovative resources within the region but also actively introduce advanced technology and personnel from the surrounding regions to promote the integration and absorption of innovation resources.

Secondly, technological progress efficiency (including the R&D of new products) should be strengthened at the high-tech enterprises of the targeted regions, including the northeast, the southern coast, the middle reach of the Yellow River, the middle reach of the Yangtze River, the southwest and the northwest. The high-tech enterprises in the regions of the northern coast and eastern coast should improve the innovation management and institutional arrangement in the HTI.

Thirdly, when providing financial support for the HTI, local governments should not only focus on the amount of investment but also the areas, links, and quality of investment. Moreover, the governments should let the market take the lead in innovation development and resource allocation in the HTI. Meanwhile, it is important to improve the sustainable and healthy development of the regional economy and foster a good technological environment. The local government should reasonably increase the number of regional high-tech enterprises and research institutions.

We are aware that this study has some limitations due to the data availability of HTI, but it can serve as a start for some potential works in the future. First, with the continuous development of environmental protection and the resource occupation of HTI in China, the environmental efficiency considering undesirable outputs can be regarded as one of our future works. Second, because of the availability of the data, this study does not propose an internal operating mechanism of the HTI. Therefore, a multi-stage model can be investigated in analysing the internal operating mechanism of the HTI in the future.

Acknowledgments

We would like to acknowledge the support from the National Natural Science Foundation of China (NSFC, Nos. 72071196, 71671181). We also acknowledge the support from the program for postgraduate education reform of the Capital University of Economics and Business (2023).

References

An, Q., F. Meng, B. Xiong, Z. Wang, and X. Chen. 2020. "Assessing the Relative Efficiency of Chinese High-Tech Industries: A Dynamic Network Data Envelopment Analysis Approach." *Annals of Operations Research*, 290 (1–2): 707–729.

Banker, R.D., A. Charnes, and W.W. Cooper. 1984. "SOME MODELS FOR ESTIMATING TECHNICAL AND SCALE INEFFICIENCIES IN DATA ENVELOPMENT ANALYSIS." *Management Science*, 30 (9): 1078–1092.

Banker, R.D., and R. Natarajan. 2008. "Evaluating Contextual Variables Affecting Productivity Using Data Envelopment Analysis." *Operations Research*, 56 (1): 48–58.

Broekel, T., N. Rogge, and T. Brenner. 2018. "The Innovation Efficiency of German Regions – a Shared-Input DEA Approach." *Review of Regional Research*, 38 (1): 77–109.

Brown, L.A., and S.-Y. Chung. 2006. "Spatial Segregation, Segregation Indices and the Geographical Perspective." *Population, Space and Place*, 12 (2): 125–143.

Carayannis, E.G., E. Grigoroudis, and Y. Goletsis. 2016. "A Multilevel and Multistage Efficiency Evaluation of Innovation Systems: A Multiobjective DEA Approach." *Expert Systems with Applications*, 62: 63–80.

Chambers, R.G., Y. Chung, and R. Färe. 1996. "Benefit and Distance Functions." *Journal of Economic Theory*, 70 (2): 407–419.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. "Measuring the Efficiency of Decision Making Units." *European Journal of Operational Research*, 2 (6): 429–444.

Chen, Jie, Shoujun Huang, and Tahseen Ajaz. 2022. "Natural Resources Management and Technological Innovation under EKC Framework: A Glimmer of Hope for Sustainable Environment in Newly Industrialized Countries." *Resources Policy*, 79 (12).

Chen, Kaihua, Yi Zhang, and Xiaolan Fu. 2019. "International Research Collaboration: An Emerging Domain of Innovation Studies?" *Resources Policy*, 48 (1): 149–168.

Chen, Xiafei, Zhiying Liu, and Qingyuan Zhu. 2020. "Reprint of 'Performance Evaluation of China's High-Tech Innovation Process :Analysis Based on the Innovation Value Chain.'" *Technovation*, 94–95 (07).

Chen, Xihui, Kienpin Tee, and Victor Chang. 2022. "Accelerating Innovation Efficiency through Agile Leadership: The CEO Network Effects in China." *Technological Forecasting and Social Change*, 179 (06).

Chen, Y., L. Ni, and K. Liu. 2021. "Does China's New Energy Vehicle Industry Innovate Efficiently? A Three-Stage Dynamic Network Slacks-Based Measure Approach." *Technological Forecasting and Social Change*, 173.

Chiu, Y.-H., C.-W. Huang, and Y.-C. Chen. 2012. "The R&D Value-Chain Efficiency Measurement for High-Tech Industries in China." *Asia Pacific Journal of Management*, 29 (4): 989–1006.

Chronopoulos, D.K., H. Liu, F.J. McMillan, and J.O.S. Wilson. 2015. "The Dynamics of US Bank Profitability." *European Journal* *of Finance*, 21 (5): 426–443.

Diaz-Balteiro, L., A. Casimiro Herruzo, M. Martinez, and J. González-Pachón. 2006. "An Analysis of Productive Efficiency and Innovation Activity Using DEA: An Application to Spain's Wood-Based Industry." *Forest Policy and Economics*, 8 (7): 762–773.

Evenson, R.E., and L.E. Westphal. 1995. Chapter 37 Technological Change and Technology Strategy. Vol. 3. *Handbook of Development Economics.*

Fagerberg, Jan, Par Hansson, Lars Lundberg, and Arne Melchior. 1997. *Technology and International Trade*. Edward Elgar Pub.

Fan, Chao, and Soe Myint. 2014. "A Comparison of Spatial Autocorrelation Indices and Landscape Metrics in Measuring Urban Landscape Fragmentation." *Landscape and Urban Planning* ,121 (01): 117–128.

Fang, Hsin-Hsiung, Hsuan-Shih Lee, Shiuh-Nan Hwang, and Cheng-Chi Chung. 2013. "A Slacks-Based Measure of Super-Efficiency in Data Envelopment Analysis: An Alternative Approach." *Omega-International Journal of Management Science*, 41 (4): 731–734.

Färe, R., E. Grifell-Tatjé, S. Grosskopf, and C.A.K. Lovell. 1997. "Biased Technical Change and the Malmquist Productivity Index." *Scandinavian Journal of Economics*, 99 (1): 119–127.

Guan, J., and K. Chen. 2010. "Measuring the Innovation Production Process: A Cross-Region Empirical Study of China's High-Tech Innovations." *Technovation*, 30 (5–6): 348–358.

Gurjar, H., A. Tripathi, and M.C. Joshi. 2021. "The Bank Efficiency through Off-Balance Sheet Items' Window: A Malmquist Approach." *Vision*, 25 (4): 448–459.

He, Y., W. Song, and F. Yang. 2021. "Research on the Supply Efficiency of Marine Ecological Products in the Yangtze River Delta Costal Urban Agglomerations Based on DEA-Tobit Model." *Sustainability* (*Switzerland*), 13 (12).

Hong, J., B. Feng, Y. Wu, and L. Wang. 2016. "Do Government Grants Promote Innovation Efficiency in China's High-Tech Industries?" *Technovation*, 57–58: 4–13.

Jiang, H., and Y. He. 2018. "Applying Data Envelopment Analysis in Measuring the Efficiency of Chinese Listed Banks in the Context of Macroprudential Framework." *Mathematics*, 6 (10).

Kalapouti, K., K. Petridis, C. Malesios, and P.K. Dey. 2020. "Measuring Efficiency of Innovation Using Combined Data Envelopment Analysis and Structural Equation Modeling: Empirical Study in EU Regions." *Annals of Operations Research*, 294 (1–2): 297–320.

Lin, C., Y.-J. Wu, C. Chang, W. Wang, and C.-Y. Lee. 2012. "The Alliance Innovation Performance of R&D Alliances - The Absorptive Capacity Perspective." *Technovation*, 32 (5): 282–292.

Liu, Chenxi, Xiaodong Zhang, Tong Wang, Guanzhou Chen, Kun Zhu, Qing Wang, and Jing Wang. 2022. "Detection of Vegetation Coverage Changes in the Yellow River Basin from 2003 to 2020." *Ecological Indicators*, 138 (05).

Liu, H.-H., G.-L. Yang, X.-X. Liu, and Y.-Y. Song. 2020. "R&D Performance Assessment of Industrial Enterprises in China: A Two-Stage DEA Approach." *Socio-Economic Planning Sciences*, 71.

Lv, C., C. Shao, and C.-C. Lee. 2021. "Green Technology Innovation and Financial Development: Do Environmental Regulation and Innovation Output Matter?" *Energy Economics*, 98.

Malmquist, S. 1953. "Index Numbers and Indifference Surfaces." *Trabajos de Estadistica*, 4 (2): 209–242.

Meng, M., and D. Qu. 2022. "Understanding the Green Energy Efficiencies of Provinces in China: A Super-SBM and GML Analysis." *Energy*, 239.

Nasierowski, W., and F.J. Arcelus. 2003. "On the Efficiency of National Innovation Systems." *Socio-Economic Planning Sciences*, 37 (3): 215–234.

Pan, Xiongfeng, Cuicui Han, Xiaowei Lu, Zhiming Jiao, and Yang Ming. 2020. "Green Innovation Ability Evaluation of Manufacturing Enterprises Based on AHP-OVP Model." *Annal of Operations Research*, 290 (1–2): 409–419.

Perelman, S. 1995. "R&D, Technological Progress and Efficiency Change in Industrial Activities." *Review of Income and Wealth*, 41 (3): 349–366.

Piao, Z., Z. Xiao, B. Miao, and R. Chen. 2017. "Innovation Performance and Influencing Factors of Expansive Listed Companies." *Eurasia Journal of Mathematics, Science and Technology Education*, 13 (12): 7755–7769.

Piao, Zhefan, Binbin Miao, Zihan Zheng, and Feng Xu. 2022. "Technological Innovation Efficiency and Its Impact Factors: An Investigation of China's Listed Energy Companies." *Energy Economics*, 112 (08).

Schumpeter, J.A. 2010. Capitalism, Socialism and Democracy. Capitalism, *Socialism and Democracy*.

Simar, L., and P.W. Wilson. 2007. "Estimation and Inference in Two-Stage, Semi-Parametric Models of Production Processes." *Journal of Econometrics*, 136 (1): 31–64.

Song, Y., T. Schubert, H. Liu, and G. Yang. 2019. "Measuring Scientific Productivity in China Using Malmquist Productivity

Index." *Journal of Data and Information Science*, 4 (1): 32–59.
Tone, K. 2001. "Slacks-Based Measure of Efficiency in Data Envelopment Analysis." *European Journal of Operational Research*, 130 (3): 498–509.
Tone, K. 2002. "A Slacks-Based Measure of Super-Efficiency in Data Envelopment Analysis." *European Journal of Operational Research*, 143 (1): 32–41.
Wang, C.-H., Y.-H. Lu, C.-W. Huang, and J.-Y. Lee. 2013. "R&D, Productivity, and Market Value: An Empirical Study from High-Technology Firms." *Omega* (*United Kingdom*), 41 (1): 143–155.
Wang, W., and C. Zhang. 2018. "Evaluation of Relative Technological Innovation Capability: Model and Case Study for China's Coal Mine." *Resources Policy*, 58: 144–149.
Wang, X., C. Sun, S. Wang, Z. Zhang, and W. Zou. 2018. "Going Green or Going Away? A Spatial Empirical Examination of the Relationship between Environmental Regulations, Biased Technological Progress, and Green Total Factor Productivity." *International Journal of Environmental Research and Public Health*, 15 (9).
Wang, Xinbin, Zilong Wang, and Rong Wang. 2023. "Does Green Economy Contribute towards COP26 Ambitions? Exploring the Influence of Natural Resource Endowment and Technological Innovation on the Growth Efficiency of China's Regional Green Economy." *Resources Policy*, 80 (01).
Wang, Y., J.-F. Pan, R.-M. Pei, B.-W. Yi, and G.-L. Yang. 2020. "Assessing the Technological Innovation Efficiency of China's High-Tech Industries with a Two-Stage Network DEA Approach." *Socio-Economic Planning Sciences*, 71.
Xiong, X., G.-L. Yang, and Z.-C. Guan. 2018. "Assessing R&D Efficiency Using a Two-Stage Dynamic DEA Model: A Case Study of Research Institutes in the Chinese Academy of Sciences." *Journal of Informetrics*, 12 (3): 784–805.
Yang, G.-L., H. Fukuyama, and K. Chen. 2019. "Investigating the Regional Sustainable Performance of the Chinese Real Estate Industry: A Slack-Based DEA Approach." *Omega* (*United Kingdom*), 84: 141–159.
Yang, G.-L., H. Fukuyama, and Y.-Y. Song. 2018. "Measuring the Inefficiency of Chinese Research Universities Based on a Two-Stage Network DEA Model." *Journal of Informetrics*, 12 (1): 10–30.
Yu, A., Y. Shi, J. You, and J. Zhu. 2021. "Innovation Performance Evaluation for High-Tech Companies Using a Dynamic Network Data Envelopment Analysis Approach." *European Journal of Operational Research*, 292 (1): 199–212.
Zhang, Chonghui, Nanyue Jiang, Tiantian Su, Ji Chen, Dalia Streimikiene, and Tomas Balezentis. 2022. "Spreading Knowledge and Technology: Research Efficiency at Universities Based on the Three-Stage MCDM-NRSDEA Method with Bootstrapping." *Technology in Society*, 68 (02).
Zhang, Chun-yan, Lin Zhao, Haotian Zhang, Meng-na Chen, Ru-yao Fang, Ying Yao, Qi-peng Zhang, and Qian Wang. 2022. "Spatial-Temporal Characteristics of Carbon Emissions from Land Use Change in Yellow River Delta Region, China." *Ecological Indicators*, 136 (03).
Zhong, K., Y. Wang, J. Pei, S. Tang, and Z. Han. 2021. "Super Efficiency SBM-DEA and Neural Network for Performance Evaluation." *Information Processing and Management*, 58 (6).
Zhong, S., and H. Wang. 2021. "The Effect of Total Factor Productivity of Forestry Industry on CO2 Emissions: A Spatial Econometric Analysis of China." *Scientific Reports*, 11 (1).
Zhou, Lei, Wen Xiao, and Na Yan. 2023. "International Comparative Research on the Relevance of Science and Technology and the Innovation Ability of the Rare Earth Industry-from the Perspective of Technology-Industry Mapping Based on Patent Information." *Resources Policy*, 80 (01).
Zou, L., X.-Z. Cao, and Y.-W. Zhu. 2021. "Research on Regional High-Tech Innovation Efficiency and Influence Factors: Evidence from Yangtze River Economic Belt in China." *Complexity*.

Appendix

Table A
The descriptive statistics of indicators in this paper.

Year	Statistics	Indicators			
		The full-time equivalent of R&D personnel	Internal expenditure on R&D	Revenue from new product sales	Patent applications
2009	Max	127449.000	1009.427	3573.153	30864.000
	Min	255.000	1.590	2.685	43.000
	Median	6308.000	43.985	123.810	870.000

Table A. (continued)

Year	Statistics	Indicators			
		The full-time equivalent of R&D personnel	Internal expenditure on R&D	Revenue from new product sales	Patent applications
2010	Mean	13880.710	108.022	490.380	2544.464
	Standard deviation	25379.810	200.688	827.210	5844.818
	Max	156235.000	1155.517	5730.897	26740.000
	Min	227.307	1.820	1.460	12.000
	Median	6025.078	50.351	128.416	691.000
2011	Mean	14247.430	123.656	553.851	2130.964
	Standard deviation	30481.800	229.732	1155.916	5089.295
	Max	179117.000	1333.247	6580.543	39338.000
	Min	274.000	1.902	5.832	54.000
	Median	6849.500	52.292	210.343	1333.000
2012	Mean	18236.930	138.510	717.217	3615.071
	Standard deviation	35511.550	263.221	1438.004	7703.026
	Max	224334.000	1572.216	7748.592	45449.000
	Min	405.000	2.293	9.319	39.000
	Median	9153.000	60.019	193.007	1689.000
2013	Mean	22252.640	164.640	830.522	4564.250
	Standard deviation	43747.000	310.388	1706.612	8918.651
	Max	208174.000	1852.199	9057.448	49691.000
	Min	473.000	2.913	13.027	58.000
	Median	9635.000	67.439	307.646	2117.000
2014	Mean	23925.500	195.383	1033.942	5104.643
	Standard deviation	41884.400	366.635	1946.266	9757.610
	Max	205106.000	2157.569	10260.970	58119.000
	Min	630.000	3.846	11.858	62.000
	Median	12053.500	79.506	386.990	2112.500
2015	Mean	25041.820	230.117	1197.904	5951.643
	Standard deviation	41913.210	426.636	2212.312	11551.280
	Max	203116.500	2465.513	12291.080	50629.000
	Min	804.800	4.876	12.537	64.000
	Median	14810.200	94.804	618.050	2400.500
2016	Mean	25946.210	266.272	1473.418	5653.143
	Standard deviation	41875.670	487.369	2642.065	10165.910
	Max	201217.700	2816.001	15714.110	64880.000
	Min	1135.000	6.701	8.372	99.000
	Median	15879.950	121.995	704.127	2610.500
2017	Mean	26072.540	307.964	1728.352	6629.321
	Standard deviation	42165.120	555.763	3291.446	12774.740
	Max	200057.000	3188.047	17778.870	84084.000
	Min	824.000	8.668	19.272	138.000

Table A. (continued)

Year	Statistics	Indicators			
		The full-time equivalent of R&D	Internal expenditure on R&D	Revenue from new product sales	Patent applications
	Median	15448.500	155.996	770.974	3185.000
	Mean	26656.960	351.573	1817.111	7986.679
	Standard deviation	41610.650	628.714	3565.199	16248.030
2018	Max	286009.800	3531.049	19158.910	105541.000
	Min	950.200	11.905	21.495	123.000
	Median	16079.150	194.479	953.840	3691.500
	Mean	30413.150	393.539	1864.632	9440.500
	Standard deviation	56466.370	696.165	3772.794	20294.920
2019	Max	277561.000	3907.878	20281.860	122963.000
	Min	616.000	14.913	7.521	99.000
	Median	16929.000	211.291	910.478	4053.500
	Mean	30719.960	436.803	1945.990	10792.210
	Standard deviation	56156.480	770.643	3956.366	23567.820

Data source: National Bureau of Statistics of China (NBSC). CSYHTI (2009-2019).

Table B1
The values of the Malmquist index for 28 provincial-level administrative regions from 2009 to 2019 in China[1].

DMUs	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
1	1.110	0.935	1.064	0.847	1.075	0.911	0.893	0.970	1.196	1.295
2	0.806	0.784	1.283	1.144	0.820	0.659	1.143	0.917	1.006	1.185
3	0.871	1.085	1.340	1.145	1.127	1.003	1.161	1.078	1.370	1.804
4	1.194	1.030	1.344	0.733	1.165	1.048	0.530	1.888	0.871	1.036
5	0.416	1.626	0.684	0.694	0.481	1.781	0.691	5.515	0.360	0.954
6	1.292	1.083	0.790	1.250	0.878	1.136	1.568	0.874	1.107	0.748
7	0.311	2.143	1.117	1.271	0.955	0.953	1.185	0.849	1.343	1.259
8	0.792	1.342	1.355	0.938	1.255	0.965	1.530	0.719	1.252	2.212
9	0.881	1.264	0.910	0.914	1.346	0.936	1.079	1.191	1.156	1.325
10	0.820	1.832	1.041	0.931	1.132	0.984	1.039	0.851	1.004	0.967
11	0.570	1.783	1.366	1.232	0.715	0.972	0.945	0.911	1.076	1.058
12	0.662	2.021	1.032	0.966	1.098	0.986	1.015	1.003	0.952	0.826
13	0.882	1.151	1.130	0.975	0.942	1.252	1.221	0.946	1.044	1.149
14	0.947	1.176	1.328	1.311	1.324	1.136	1.690	1.093	1.250	1.148
15	1.022	1.115	1.024	0.920	1.074	1.303	1.138	1.173	0.829	0.966
16	0.595	1.695	0.960	5.646	1.033	1.014	0.965	1.002	0.989	0.680
17	0.829	1.338	1.196	1.049	1.107	1.344	1.340	1.091	1.472	1.174

[1] The numbers 1-28 in the Table B1-B3 and Figure A represent the following provincial-level administrative regions: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu and Ningxia.

Table B1. (continued)

DMUs	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
18	0.831	2.886	0.795	1.470	0.777	0.917	1.173	0.836	1.092	1.100
19	1.166	1.001	1.058	1.099	1.057	0.982	1.274	1.260	1.020	1.075
20	0.727	2.122	0.883	1.392	0.823	1.004	1.205	1.524	1.286	1.138
21	0.135	11.047	1.094	0.861	0.576	0.952	0.583	3.527	0.688	0.956
22	0.698	2.333	0.614	0.909	1.571	1.435	0.746	1.129	0.825	0.922
23	0.388	3.971	0.847	0.780	1.718	0.921	1.020	0.839	0.719	1.515
24	1.151	0.934	1.117	0.932	1.246	1.353	1.810	1.028	1.171	0.962
25	0.443	1.655	0.717	0.947	1.069	0.693	1.343	1.137	1.004	0.866
26	1.088	1.295	0.906	0.946	1.212	1.323	1.246	0.998	0.907	1.513
27	1.392	0.823	1.331	0.859	1.167	1.172	0.783	1.353	1.023	0.865
28	0.503	1.512	0.909	1.084	0.301	1.229	1.537	0.635	1.049	1.007

Table B2
The values of TC for 28 provincial-level administrative regions from 2009 to 2019 in China.

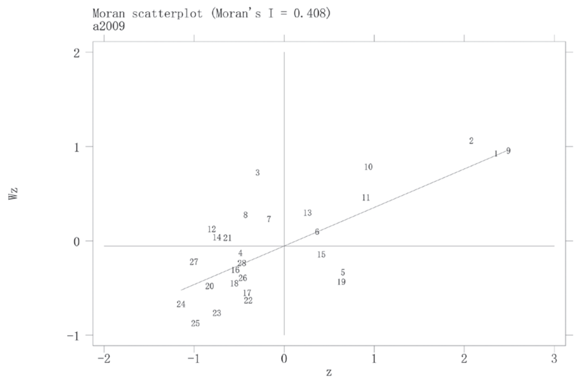
DMUs	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
1	0.957	0.978	1.107	0.960	1.069	0.953	1.038	1.279	0.877	1.072
2	0.836	1.178	1.023	1.127	0.968	1.047	1.008	1.269	0.901	1.123
3	0.820	1.253	1.001	1.386	0.969	1.192	0.932	1.219	0.860	1.015
4	0.743	1.546	0.719	2.055	0.876	1.223	0.838	0.902	0.826	0.915
5	0.368	0.666	0.684	0.921	0.973	1.451	0.835	0.929	0.730	0.989
6	0.989	0.732	1.103	1.232	0.853	1.184	0.856	1.400	0.819	1.043
7	0.678	1.203	0.852	1.635	0.922	1.194	0.891	1.475	0.760	1.013
8	0.879	0.758	1.146	1.319	0.877	1.184	0.923	1.298	0.808	0.957
9	0.964	1.294	1.089	1.062	1.091	0.972	1.086	1.355	0.850	1.186
10	1.145	1.165	1.022	1.035	1.102	0.987	1.082	1.038	1.004	1.043
11	0.753	1.402	1.191	0.873	1.096	0.755	1.078	1.036	1.032	0.935
12	0.561	1.873	1.057	1.005	1.052	1.017	0.986	1.052	1.005	0.918
13	0.857	1.230	1.089	1.115	1.095	1.042	1.072	1.255	0.866	0.977
14	0.795	1.117	1.076	1.333	0.886	1.245	0.877	1.450	0.834	0.897
15	1.001	1.141	1.058	1.003	1.097	1.029	1.194	1.259	0.811	1.097
16	0.641	1.744	0.975	1.472	0.996	1.118	0.936	1.084	0.892	0.857
17	0.867	1.070	1.117	1.350	1.061	1.083	1.026	1.345	0.859	1.108
18	0.851	0.957	1.222	1.165	0.893	1.092	1.016	1.154	0.919	0.903
19	0.906	1.496	1.067	1.056	1.128	0.986	1.156	1.043	0.936	1.042
20	0.798	1.311	0.822	1.375	0.862	1.178	0.880	1.677	0.641	1.043
21	0.426	0.677	2.808	1.763	0.697	1.277	1.015	1.338	0.683	0.799
22	0.748	1.280	0.979	1.231	0.972	1.134	0.868	1.144	0.905	0.838
23	0.854	0.823	1.324	0.850	1.048	0.919	1.011	1.460	0.882	0.925
24	0.844	1.198	0.893	2.202	0.989	1.212	0.872	1.459	0.765	0.874
25	0.796	1.550	0.726	1.695	0.891	1.179	0.908	1.473	0.774	0.734

Table B2. (continued)

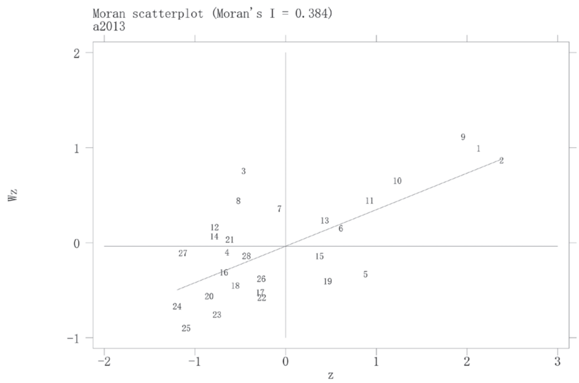
DMUs	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
26	0.885	1.041	1.133	1.311	1.058	1.138	1.007	1.228	0.850	0.878
27	0.781	0.976	1.050	1.370	0.864	1.180	0.890	1.271	0.748	0.885
28	0.547	0.737	0.714	1.247	0.977	1.356	0.792	0.858	0.651	0.676

Table B3
The values of EC for 28 provincial-level administrative regions from 2009 to 2019 in China.

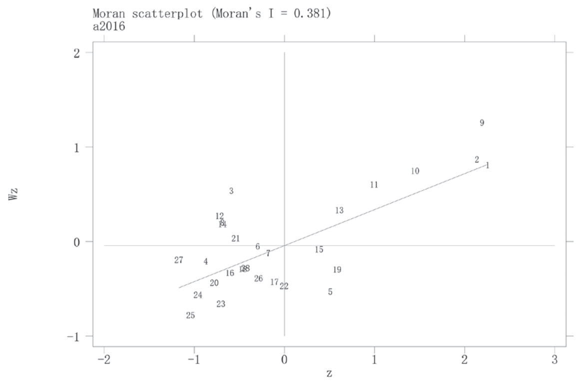
DMUs	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
1	1.160	0.956	0.961	0.882	1.006	0.955	0.861	0.758	1.364	1.208
2	0.965	0.665	1.255	1.015	0.847	0.630	1.133	0.723	1.116	1.056
3	1.063	0.866	1.339	0.826	1.164	0.841	1.246	0.884	1.594	1.778
4	1.606	0.666	1.869	0.357	1.329	0.856	0.632	2.094	1.055	1.133
5	1.131	2.441	1.000	0.754	0.494	1.228	0.828	5.939	0.493	0.965
6	1.307	1.479	0.716	1.014	1.029	0.960	1.832	0.624	1.351	0.718
7	0.458	1.781	1.311	0.777	1.035	0.798	1.329	0.576	1.767	1.243
8	0.901	1.770	1.182	0.711	1.431	0.815	1.657	0.554	1.549	2.310
9	0.914	0.977	0.836	0.861	1.234	0.963	0.993	0.879	1.359	1.117
10	0.716	1.572	1.019	0.900	1.027	0.998	0.961	0.820	1.000	0.927
11	0.757	1.272	1.146	1.411	0.652	1.287	0.876	0.879	1.043	1.132
12	1.181	1.079	0.976	0.961	1.044	0.969	1.029	0.953	0.947	0.899
13	1.029	0.936	1.038	0.874	0.860	1.202	1.138	0.754	1.206	1.176
14	1.190	1.053	1.235	0.983	1.493	0.912	1.927	0.754	1.498	1.279
15	1.021	0.977	0.968	0.917	0.979	1.266	0.953	0.932	1.022	0.881
16	0.928	0.972	0.984	3.835	1.036	0.906	1.031	0.924	1.109	0.793
17	0.957	1.250	1.071	0.777	1.044	1.241	1.306	0.811	1.713	1.060
18	0.976	3.015	0.650	1.262	0.870	0.840	1.154	0.725	1.189	1.218
19	1.287	0.669	0.991	1.041	0.937	0.997	1.102	1.208	1.090	1.032
20	0.911	1.618	1.075	1.013	0.955	0.852	1.370	0.908	2.006	1.091
21	0.316	16.314	0.390	0.488	0.827	0.745	0.574	2.636	1.008	1.196
22	0.933	1.822	0.627	0.739	1.617	1.266	0.859	0.987	0.912	1.100
23	0.455	4.825	0.640	0.917	1.639	1.002	1.009	0.575	0.815	1.638
24	1.364	0.780	1.251	0.423	1.260	1.116	2.077	0.705	1.531	1.100
25	0.557	1.068	0.987	0.559	1.200	0.587	1.480	0.772	1.297	1.179
26	1.229	1.244	0.800	0.722	1.145	1.163	1.237	0.813	1.067	1.724
27	1.783	0.844	1.268	0.627	1.350	0.993	0.879	1.065	1.368	0.977
28	0.920	2.053	1.273	0.869	0.308	0.907	1.942	0.740	1.612	1.490



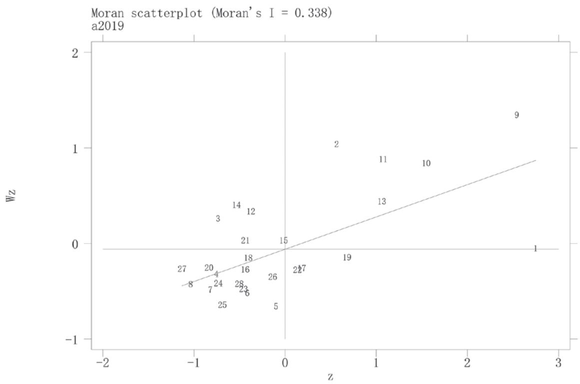
(a) The Moran index in 2009



(b) The Moran index in 2013



(c) The Moran index in 2016



(d) The Moran index in 2019

Fig. A. The Moran scatter diagrams of the HTI.