Research on the Regional Differences and Influencing Factors of the Innovation Efficiency of China's High-Tech Industries: Based on a Shared Inputs Two-Stage Network DEA

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Abstract: Innovation ability has become one of the core elements in the pursuit of China's green growth, and high-tech industries are playing a leading role in technological innovation in China. With the rapid development of China's high-tech industries, their innovation efficiency has attracted widespread attention. This article aims to illustrate a shared inputs two-stage network Data Envelopment Analysis (DEA), to measure the innovation efficiency of high-tech industries in China's 29 provinces from 1999 to 2018. The results indicate that there are obvious differences in the innovation efficiency of the provinces. The technology development efficiency, the technical transformation efficiency, and the overall innovation efficiency of the developed east coast provinces are generally higher than those of the backward central and western provinces. This article further applies the spatial econometrics model to analyze the factors influencing the innovation efficiency of high-tech industries. We have found that government support, R&D input intensity, industries aggregation, economic extroversion, and the level of development of the modern service industries cause varying degrees of impact on innovation efficiency.

Keywords: high-tech industries; innovation efficiency; regional difference; two-stage network DEA

1. Introduction

Since the implementation of the reform leading to a more open international policy, China has witnessed rapid economic development, with an average annual growth rate of 9.6% between 1978 and 2018. However, this mode of extensive economic growth pursues rapid economic growth one-sidedly and ignores the quality of economic growth, generating serious resource waste, environmental pollution and environmental damage. It is very important for the Chinese government to promote an ecological society while exploring the path of economic development. The Chinese government has set a goal of High-quality Development that is an organic combination of China's national conditions and green growth [1], and has ratified over 30 conventions and protocols related to environmental protection, which cover every aspect of economic development and environmental regulations, as of 2017.

The concept of "green growth" has attracted considerable worldwide attention since it was first put forward by the Economic and Social Commission for Asia and the Pacific, at the United Nations Economic and Social Commission for Asia and the Pacific Conference (UNESCAP) in 2005 [2]. According to the Organization for Economic Cooperation and Development (OECD), green growth can help to mitigate environmental pollution, biodiversity loss and climate changes, and promote a sustainable use of resources and the environment while fostering economic growth and development [3]. The Porter Hypothesis made scholars and policymakers realize that appropriate environmental

regulations can motivate enterprises to make technological changes, improve competitiveness, and promote production efficiency, thus providing a path for green economy [4,5]. It seems that the compliance pressure and additional income from green product innovation and process innovation will encourage enterprises to carry out technological innovation [6], thereby improving the overall technical efficiency and competitiveness of the industries and achieving the goals of energy-saving and carbon emission reduction [7,8]. Promoting the Chinese economy ultimately contributes to green growth transformation [9,10].

The Chinese government, regarding independent innovation as the core of its national development strategy and the key to enhancing its comprehensive national strength in 1990s, began to speed up the promotion of high-tech industries and transformed the method of promoting economic growth from the form mainly relying on material resource consumption to that relying on scientific and technological progress, targeting the quality improvement of workers and management innovation at the same time [11]. Such measures have opened up a new situation in the development of high-tech industries in China. As a result, China's high-tech industries have grown at an annual average of over 16% in the 21st century, and the output value accounted for approximately 20% of GDP in 2018, according to the China Statistics Yearbook on High Technology Industry. Indeed, high-tech industries have become an important power in the New Normal Stage of social economic development in China.

Meanwhile, different types of high-tech industries in different cities are facing differences in terms of economic basis, resource endowment, and social and ecological environment [12]. There are serious regional differences between the eastern and central and western regions, especially in the level of technology, R&D investment and talent structure, which are related to the innovation of high-tech industries [13]. The differences between resource allocation may lead to different outputs and give rise to an imbalance in regional development in an interactive way: high-tech industries support and drive regional economic green growth, become the driver of regional industrial structure upgrade, stimulate and strengthen the technological innovation and institutional innovation of the regional economy; in turn, the regional economic foundation provides an important support for the development of high-tech industries. The regional resource endowment and resource allocation capabilities have been the key conditions for the innovation development of high-tech industries [14,15]. With China's rapid development, the regional imbalance within China's high-tech industries has become even more prominent. Does the regional imbalance in the development of China's high-tech industries cause a regional difference in innovation efficiency? If there is a difference, what are the factors? Measuring the innovation efficiency of China's high-tech industries, objectively and scientifically, and then exploring the reasons as to why there are regional differences is a theoretically important effort, which can contribute to strengthening the competitive advantage of the nation's high-tech industries and technology innovation ability.

This study has the following aims: first, to build a more suitable and scientific method to calculate the innovation efficiency of high-tech industries in China; second, to solve the problem of verifying the regional difference of China's high-tech industries' innovation efficiency; third, to identify the main factors affecting the regional differences in innovation efficiency. In this paper, we have employed a shared inputs two-stage network Data Envelopment Analysis (DEA) model to measure the innovation efficiency of the high-tech industries in China's 29 provinces from 1999 to 2018 and to analyze the factors influencing innovation.

We arranged the rest of this paper as follows: Section 2 presents the theoretical hypothesis proposed by this article; Section 3 refers to the theoretical analysis of the methods we will use, and then selects variables and data for the model; Section 4 presents the results of the empirical analysis and a total introduction to the results that were estimated; Section 5 aims to find the main influencing factors of China's high-tech industries' innovation efficiency with the Spatial Econometrics Model; Section 6 summarizes the research conclusions and puts forward the relevant policy suggestions based on them.

2. Theoretical Hypothesis

Many studies in the literature focus on innovation efficiency and the factors influencing China's high-tech industries. Guan and Chen employed a relations network DEA to estimate the efficiency of China's high-tech industries' innovation and R&D areas, by using its high-tech industries area data [16]. Michael et al. applied the Germ-Parameter's approach to analyze the influence of R&D upon the productivity of China's high-tech industries and found that there is a regional difference in the influence of R&D investment and technological progress on the productivity of the nation's high-tech industries [17]. Yang looked at the R&D innovation efficiency of high-tech industries and its influencing factors, taking China's high-tech industries' regional panel data during 1995–2009 and applying the stochastic frontier model [18]. Liu and Zhang used a three-stage DEA model to measure the innovation efficiency of foreign-invested and state-owned enterprises in China's high-tech industries, while excluding the impacts of environmental variables such as government funding, qualification of technical personnel, R&D atmosphere, average enterprise scale, and hardware base in the industries [19]. Chen and Meng combined a network SBM model with a DEA window analysis to measure the technological innovation efficiency of China's high-tech industry during 2000–2011. The research indicated a rising trend in the overall efficiency of the technological innovation of the high-tech industry in the past 10 years, and showed that the outbreak of the financial crisis had a negative impact on the efficiency of technological innovation in the short term [20].

Zhou et al. took China's 56 national high-tech zones as the research objects and discussed the decomposition, features, and diversity issues of the operational efficiency of the high-tech zones, based on a DEA evaluation of their comprehensive efficiency, pure technical efficiency, and scale efficiency. They found that the operating efficiency of China's high-tech zones characterizes their cycle development, and that the low efficiency of the "first entrepreneurship" and "secondary entrepreneurship" stages results from their invalid scale efficiency and pure technical efficiency [21]. Liu and Ning utilized the panel data of Chinese intelligent manufacturing enterprises during 2010–2013 to evaluate their technology innovation efficiency. The study showed that the average technology innovation efficiency of intelligent manufacturing industries was in the rising stage, but the overall efficiency was still relatively low [22]. Fu and Jiang applied a Fuzzy-Set Qualitative Comparative Analysis (fs-QCA) to conduct a multiple-case analysis with a triple helix dynamic cooperation model (university-industry-government) and found positive effects of multiple participants on regional radical innovation in China [23].

Meanwhile, when the above literature measures the innovation efficiency of China's high-tech industries, a decision making unit (DMU) is considered a "black box", and these studies only consider the external characteristics of the DMU, ignoring its internal structure. Therefore, the result has some deviations and does not reflect the real situation of high-tech industries. Fare and Grosskopf proposed a network DEA, decomposed the DMU into a "gray box", found the inside efficiency of the production process while evaluating the DMU's overall efficiency, and enhanced the separability of the evaluation results [24]. Since then, many scholars have begun to study the production process with a two-phase structure.

Cook et al. pointed out a two-stage process in the banking industries. In the first stage, a bank produces intermediate variables, deposits, through the consumption of fixed assets, labor, and investment in information technology. In the second stage, the bank uses the deposits to produce loan and profit [25]. Seiford and Zhu studied the marketing and profitability of Fortune 500 companies [26]. Kao and Wang applied the analysis of the two-stage process to Taiwan's non-life insurance industries [27]. Chen and Guan made use of the transforming information of the intermediate product and the configuration information of the input factors to build a two-stage network DEA efficiency measurement and decomposition model that has shared inputs under the hypothesis of constant returns to scale and variable returns to scale [28]. Rui et al. built up the shared inputs two-stage network DEA model based on the output of scientific and technological achievements of high-tech industries and inputted the scientific and technological achievements into productive forces [29].

Lu et al. presented an application of a two-stage network DEA for examining the performance of 30 U.S. airline companies [30]. Ye and Liu suggested that a network DEA can calculate not only the efficiency of a system and its subprocesses, but also the production information embedded in the intermediate products, as well as the allocation information of various inputs among the individual subprocesses. While maintaining a high level of R&D investment, it is necessary to increase the ability to transform scientific and technological achievements [31].

Therefore, theoretical Hypothesis 1 is proposed in this paper:

Hypothesis 1. *The shared inputs Two-stage Network DEA Model is more appropriate to reflect the internal structure characteristics of the DMUs when calculating the innovation efficiency of high-tech industries, thereby accurately showing the regional differences.*

Current research on the factors influencing the regional differences in the innovation efficiency of China's high-tech industries has given priority to empirical research models, overlooking the analysis of the influencing factors and mechanisms. Liu and Buck used a panel data analysis to empirically investigate the impact of different channels for international technology spillover on the innovation performance of Chinese high-tech industries. They found that both international technology spillover sources and indigenous efforts jointly determine the innovation performance of Chinese high-tech sectors [32]. Feng et al., based on the panel data of large and medium-sized industrial enterprises in China from 2005 to 2007, used a stochastic frontier (SFA) analysis to study the impact of domestic technology purchases, foreign technology introduction, and foreign-funded enterprise technology activity spillover on regional industrial innovation performance. They found significant differences and imbalances in the eastern, central, and western regions [33]. Yin applied network SBM and Tobit models to evaluate and analyze the innovation efficiency of China's high-tech industries, and found that regional economic strength, industrial structure, and government support can significantly improve the regional innovation efficiency [34]. Li et al. applied a convergence model to analyze the innovation efficiency differences and their changing trends in Chinese provinces. Based on data regarding the innovation efficiency of high-tech industries from 2002 to 2011, they point out that technological labor capital and high-tech capital are the conditional convergence factors for the overall regional differences [35]. Chen, Heng, et al. constructed the evaluation index system of technological innovation efficiency using a DEA model with the data of 28 provincial regions from 2008 to 2014, and evaluated the efficiency of high-tech industries. They found regional differences between provinces and pointed out that they may result from the utilization rate of innovation resources [36]. Liu et al. constructed an improved SBM-DEA model to measure the green technology innovation efficiency of China's high-tech industries by dividing the regions of China into four clusters, and study the influence degree and regional differences of various influencing factors through quantile regression method. The research shows that the factors significantly affecting green innovation efficiency are different in various regions [37].

These studies are rich and detailed, including different perspectives, different regions, and different methods. However, most studies focus on how to measure the effectiveness of high-tech industry innovation efficiency, lacking an in-depth analysis of the factors responsible for the regional differences in technical innovation. Accordingly, we planned to measure the factors that affect the regional differences based on the results of Hypothesis 1, through a spatial econometric model. This led us to propose a second theoretical hypothesis:

Hypothesis 2. *Government support, R&D input intensity, industries aggregation, economic extroversion, and the development level of modern service industries are the main factors causing the regional differences in China's High-tech Industries' Innovation Efficiency.*

3. Materials and Methods

3.1. Brief Introduction to the Research Approach

To reach the goals set above, we designed the research approach of this paper as follows. Firstly, an analysis of the features of the innovation process to select a suitable model. The innovation process of high-tech industries is divided into the technical development phase and the technical transformation phase, and the intellectual, scientific, and technological achievements are the intermediate variables of innovation in high-tech industries, which is to say that the output of the technical development phase is the input of the technical transformation phase. Secondly, this paper uses the shared inputs two-stage network DEA model to measure the innovation efficiency of high-tech industries in China's 29 provinces from 1999 to 2018, to analyze the regional differences in the innovation efficiency of high-tech industries and calculate the technology development efficiency, the technical transformation efficiency, and the overall innovation efficiency. Thirdly, we have built a spatial econometric model to analyze the impact of government support, R&D input intensity, industries aggregation, economic extroversion, and the level of development of modern service industries on the innovation efficiency of high-tech industries, and to explore the reasons for the regional differences in innovation efficiency of China's high-tech industries.

3.2. Methods: Shared Inputs Two-Stage Network DEA

According to Fare's network DEA, the technological innovation process can be divided into two stages [24]. The first stage is technological development, which transforms innovation input into intellectual scientific-technology (sci-tech) achievements. The second stage is technological conversion, which is the industrialization of intellectual sci-tech achievements. Therefore, innovation input (sci-tech achievements) and the industrialization of those sci-tech achievements form the whole technological innovation system, whose efficiency reflects the innovation ability. Technological development efficiency shows the ability to use human resources and capital for innovation, while technological conversion efficiency reveals the ability to use technology for commercialization and marketization of sci-tech achievements (as shown in Figure 1).
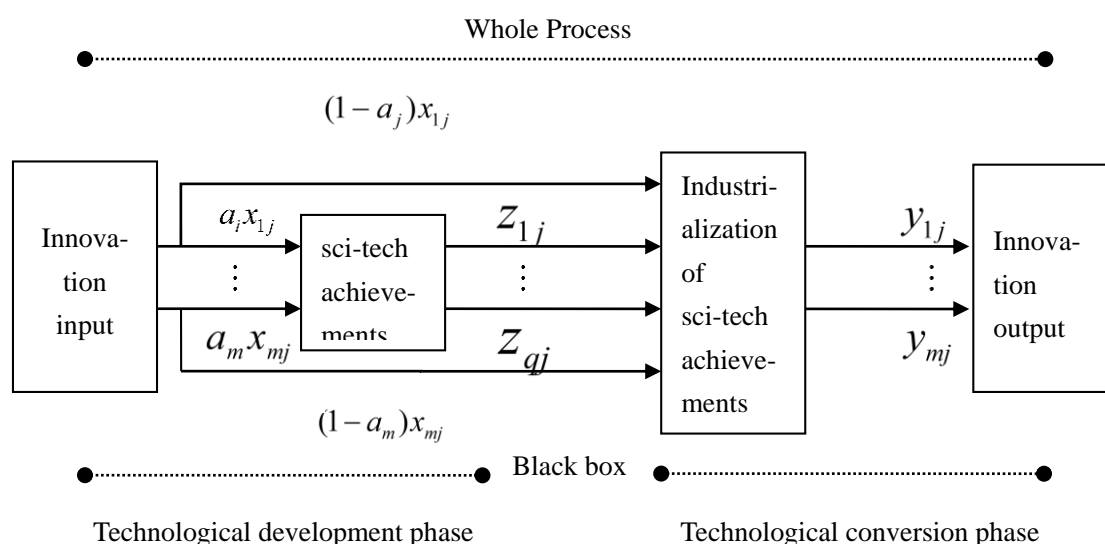

Figure 1. Shared input innovation process.

Suppose that there are n DMU, and each DMU_j is equipped with initial input x_{ij}, s final output y_{sj}, and q intermediate product z_{qj}. The following two points should be taken into account. First, initial input x_{ij} does not run out in the first stage, being allocated instead in the two subprocesses, in some proportion that differs from the difference of the DMU. The discretionary input of x_{ij} in the first

stage is $\alpha_i x_{ij}$, and $(1-\alpha_i)x_{ij}$ is used for the discretionary input in the second stage. Second, the re-input of intermediate products should be considered. In the whole process, intermediate product z_{qj} is the output of the first stage as well as the input of the second stage.

Referring to Castelli's method of model setting, this paper structures the shared inputs two-stage network DEA model as follows [38]. Decision variables v_i^1 and v_i^2 ($i = 1, 2, \cdots, m$) respectively represent the weight of the two parts' input in the process. In addition, ω_p^1 and $\omega_p^2(p = 1, 2, \cdots q)$ are respectively the output of intermediate product z_{qj} in the first stage and the weight of the input in the second stage. The weight of output y_{sj} is presented as decision variable $u_r(r = 1, 2, \cdots, s)$. In accordance with Charnes' theory of the DEA ratio model [39], the holistic technology efficiency of the DMU in output growth is expressed in Appendix A. Then, after using the Charnes–Cooper transformation [39,40], we could get the mathematical programming model directly on the assumption of VRS.

To facilitate calculation, the non-linear programming should be transformed into linear programming as follows:

$$E = \max \sum_{p=1}^{q} W_p^1 Z_{pk} + \sum_{r=1}^{s} U_r Y_{rk} - u_k^A - u_k^B$$

$$s.t. \begin{cases} \sum_{i=1}^{m} \pi_i^1 X_{ik} + \sum_{i=1}^{m} V_i^2 X_{ik} + \sum_{i=1}^{m} \pi_i^2 X_{ik} + \sum_{p=1}^{q} W_p^2 Z_{pk} = 1 \\ \sum_{i=1}^{m} \pi_i^1 X_{ij} - (\sum_{p=1}^{q} W_p^1 Z_{pj} - u_k^A) \geq 0 \quad j = 1, 2, \cdots, n \\ \sum_{i=1}^{m} V_i^2 X_{ij} - \sum_{i=1}^{m} \pi_i^2 X_{ij} + \sum_{p=1}^{q} W_p^2 Z_j - (\sum_{r=1}^{s} U_r Y_{rj} - u_k^B) \geq 0 \quad j = 1, 2, \cdots, n \\ \pi_i^2 \geq V_i^2 \geq \varepsilon \quad \pi_i^2, W_p^1, W_p^2, U_r \geq \varepsilon \quad i = 1, 2, \cdots, m \end{cases} \tag{1}$$

Formula (1) describes the input-oriented *DMU* holistic technology efficiency measuring model. Once the optimal combinations of decision variables $\alpha_i(\alpha_i = \pi_i^2 / V_i^2)$, $V_i^1(V_i^1 = \pi_i^1 / \alpha_i)$, V_i^2, W_p^1, W_p^2, U_r, u_k^A and u_k^B) are obtained through Formula (1), the value of the technology efficiency of the first stage and the second stage in the production process could be calculated by Formulae (2) and (3).

$$E^1 = \frac{\sum_{p=1}^{q} \omega_p^1 Z_{pk} - u_k^1}{\sum_{i=1}^{m} v_i^1 \alpha_i X_{ik}} = \frac{\sum_{p=1}^{q} W_p^1 Z_{pk} - u_k^A}{\sum_{i=1}^{m} V_i^1 \alpha_i X_{ik}} \tag{2}$$

$$E^2 = \frac{\sum_{r=1}^{s} u_r Y_{rk} - u_k^2}{\sum_{i=1}^{m} v_i^2 (1-\alpha_i) X_{ik} + \sum_{p=1}^{q} \omega_p^2 Z_{pk}} = \frac{\sum_{r=1}^{s} U_r Y_{rk} - u_k^B}{\sum_{i=1}^{m} V_i^2 (1-\alpha_i) X_{ik} + \sum_{p=1}^{q} W_p^2 Z_{pk}} \tag{3}$$

3.3. Selection of Variables

As regards the inputs in the process of technological development, as the latter transforms innovation resources into intellectual sci-tech achievements, the core elements of technological development consist of R&D researchers and R&D capital. This paper selects the full-time equivalents of the high-tech industries' R&D researchers as the input variables and the internal expenditure of the high-tech industries' R&D expense as the input variable of R&D capital. Owing to the influence of the input of R&D expense in each stage on the output of technological innovation, this paper transforms the internal expenditure of R&D expense into internal expenditure stock to measure the R&D input. The specific calculation is $K_t = \theta_{(t-1)} + (1 - \delta)K_{(t-1)}$, where K_t is the internal expenditure of R&D expense of a certain province's high-tech industries in year t, δ is the depreciation rate of R&D capital, and θ_{t-1} is the discounted R&D input of the high-tech industries in year $t - 1$. Suppose that the growth

rate of the high-tech industries' R&D expense is equal to that of the R&D expense input. The initial value of the R&D expense input can be set as $K_0 = \theta_0/(g + \delta)$, where g is the annual growth rate of the R&D expense input. Like most scholars, we considered the depreciation rate of R&D capital to be $\delta = 15\%$.

As regards the outputs in the process of technological development and the inputs in the process of technological conversion, the former are mainly intellectual sci-tech achievements, including patent technology and non-patent technology. A patent, which involves the legal protection of sci-tech knowledge, is a formally recognized innovative product. As a commercial secret of enterprises, non-patent technology is not protected in legal form and is mainly used for improving the production process and competitiveness. The inputs of this process are the outputs of technological development. Sci-tech achievements can be obtained in technological innovation activities and through transactions in the technology market, while a commercial secret is not available through those methods. Therefore, this paper selects the turnover in patents and the technology market as the outputs of technological development and the inputs of technological conversion.

As regards the outputs of technological conversion, since the latter amounts to the process of industrializing intellectual sci-tech achievements, it involves product innovation achievements and process innovation achievements. This paper uses the sales revenue of a new product to measure product innovation and the total output value of high-tech industries to measure process innovation.

3.4. Introduction of Data

This paper selects 29 Chinese provinces (autonomous regions and municipalities: hereinafter referred to as provinces) from 1999 to 2018 as the analyzing samples, Tibet and Xinjiang are excluded due to serious data shortages, and Taiwan, Hong Kong, and Macao are not included in the scope of the analysis. The data come from the China Statistical Yearbook, China Statistics Yearbook on High Technology Industry, and the relevant statistical yearbooks of these provinces. Regarding default data, this paper completes the mean of the data referring to the year before and after. As the State Council did not approve the establishment of Chongqing as a municipality directly under the central government until 1997, data on Chongqing's high-tech industries in 1997 are taken from the Chongqing Statistical Yearbook and relevant government gazettes.

Due to the long time span of the data, and to avoid the influence of inflation and deflation on price-related time series data, this paper uses a fixed assets investment index to conduct a price deflator to index sequential data of price-related new product value and internal expenditure of R&D expense. We then transform the data calculated with current prices into the data calculated with prices in 1995. Generally speaking, in technological development there is a time lag between resource input and technological achievements, as well as the industrialization of sci-tech achievements. Consequently, the data of the initial input, intermediate output, and final output in this paper are respectively those of years t, $t + 1$, and $t + 2$, meaning that the input index of technological development is selected from the data from 1996 to 2016, the output index of technological development from the data from 1997 to 2017, and the final output index of technological innovation from the data from 1998 to 2018.
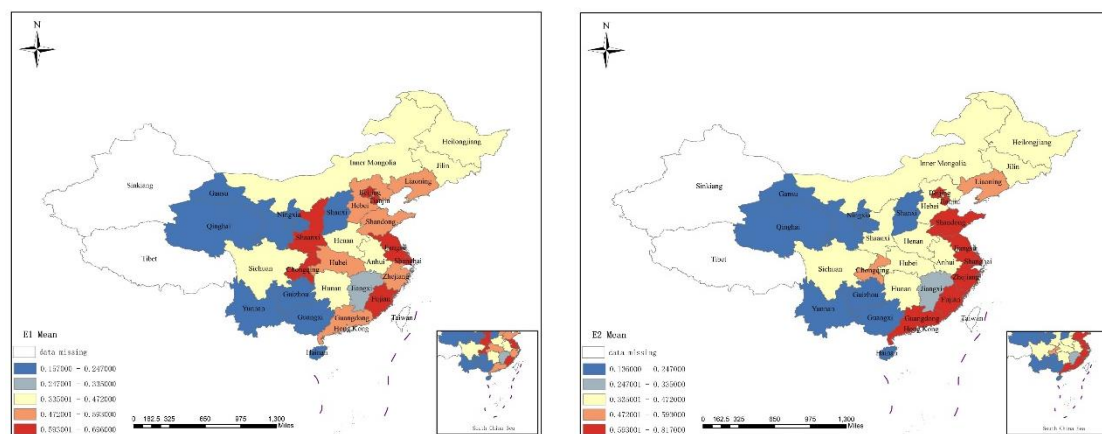
4. Results

This paper uses DEA-solver 6.0 to estimate the innovation efficiency of high-tech industries from 29 Chinese provinces from 1999 to 2018. Table 1 lists the results, and the value of E^1 and E^2 are expressed on the maps shown in Figure 2.

Table 1. Estimated results of China's high-tech industries' innovation efficiency.

Province	E^1		E^2		E	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Beijing	0.696	0.206	0.802	0. 352	0.733	0.201
Tianjin	0.613	0.314	0.709	0.291	0.691	0.313
Hebei	0.520	0.227	0.465	0.209	0.491	0.285
Liaoning	0.571	0.190	0.538	0.186	0.546	0.175
Shandong	0.579	0.178	0.595	0.212	0.590	0.302
Shanghai	0.688	0.242	0.817	0.301	0.726	0.219
Jiangsu	0.627	0.209	0.763	0.238	0.689	0.190
Zhejiang	0.541	0.236	0.746	0.233	0.632	0.234
Fujian	0.614	0.301	0.775	0.281	0.678	0.340
Guangdong	0.593	0.332	0.784	0.304	0.701	0.264
Guangxi	0.207	0.117	0.229	0.201	0.221	0.178
Hainan	0.157	0.104	0.234	0.124	0.199	0.054
Shanxi	0.242	0.112	0.220	0.114	0.231	0.095
Inner Mongolia	0.415	0.231	0.403	0.240	0.413	0.262
Jilin	0.456	0.196	0.418	0.189	0.435	0.134
Heilongjiang	0.431	0.189	0.406	0.172	0.422	0.157
Anhui	0.420	0.205	0.377	0.230	0.393	0.313
Jiangxi	0.335	0.242	0.303	0.218	0.312	0.305
Henan	0.434	0.207	0.411	0.194	0.425	0.163
Hubei	0.562	0.296	0.435	0.251	0.507	0.252
Hunan	0.433	0.168	0.398	0.186	0.410	0.139
Shaanxi	0.631	0.263	0.465	0.237	0.538	0.245
Gansu	0.224	0.173	0.189	0.123	0.206	0.153
Qinghai	0.173	0.118	0.136	0.102	0.145	0.064
Ningxia	0.212	0.109	0.194	0.115	0.201	0.181
Chongqing	0.606	0.272	0.569	0.263	0.585	0.332
Sichuan	0.472	0.240	0.388	0.254	0.412	0.284
Yunnan	0.247	0.119	0.199	0.113	0.238	0.091
Guizhou	0.186	0.105	0.167	0.132	0.172	0.159

Note: Due to space limitation, this table only lists the mean and standard deviation of the provinces' high-tech industries' innovation efficiency from 1999 to 2018.

Figure 2. The value of technology efficiency of the first stage and the second stage.

The findings from the estimated results of technological development efficiency, technological conversion efficiency, and holistic innovation efficiency are as follows.

First, judging from the technological development efficiency (E^1), the technological development efficiency of the high-tech industries in Beijing, Shanghai, and Shaanxi is high and respectively 0.696, 0.688, and 0.631, while that in Hainan, Qinghai, and Guizhou is low and respectively 0.157,

0.173, and 0.186. As the main locations of China's institutions of higher learning, Beijing, Shanghai, and Shaanxi are equipped with sufficient high-end technical talent, which may result in a high technological development efficiency. However, in backward provinces like Hainan, Qinghai, and Guizhou, the shortage of research institutions and high-end technical talent brings about a low technological development efficiency.

Second, the results of technological conversion efficiency (E^2) show that the technological conversion efficiency of the high-tech industries in Shanghai, Beijing, and Guangdong is high, while that in Qinghai, Guizhou, and Gansu is low. In developed provinces, such as Shanghai, Beijing, and Guangdong, the degree of market opening is higher, and modern service industries are relatively intact, with an active technology market that contributes to the industrialization of intellectual sci-tech achievements. In contrast, in western provinces like Qinghai, Guizhou, and Gansu, the lack of innovation resources leads to the high cost of innovation and low technological conversion efficiency.

Third, judging from the holistic efficiency (E), the provinces' high-tech industries distinctly differ in innovation efficiency, which in eastern coastal provinces is usually higher than that of central and western provinces. For example, the gap between Beijing's and Qinghai's innovation efficiency reaches 0.588. The high-tech industries' technological innovation is a complex indicator, and the efficiency, influenced by many factors, is the symbol of a region's economic and social strength. Consequently, the innovation efficiency of high-tech industries in backward regions is relatively low.

Fourth, a comparison of the three kinds of efficiency shows that in backward provinces, technological development efficiency is higher than holistic innovation efficiency, which is higher than technological conversion efficiency. For example, technological development efficiency, technological conversion efficiency, and holistic innovation efficiency in Guizhou Province are respectively 0.172, 0.186, and 0.167. In developed provinces, among the three kinds of efficiency, technological conversion efficiency is the highest, followed by holistic innovation efficiency, and technological development efficiency is the lowest. For example, technological development efficiency, technological conversion efficiency, and holistic innovation efficiency in Shanghai are respectively 0.726, 0.688, and 0.817. This indicates that in developed regions, a higher technological conversion efficiency promotes the holistic innovation efficiency of high-tech industries, while in backward regions, a lower technological conversion efficiency restrains, to some extent, the holistic innovation efficiency of these industries.

5. Discussion

The above-mentioned analysis shows that the innovation efficiency of China's high-tech industries in different regions differs considerably. What are the resulting factors? Based on the measurement of high-tech industries' innovation efficiency, this paper explores the influencing factors.

5.1. Main Influencing Factors of China's High-Tech Industries' Innovation Efficiency

The innovation of high-tech industries depends on a complicated engineering system, influenced by many factors. Referring to the conclusions of the existing literature, this paper mainly analyzes the effect of government support, R&D input intensity, industries agglomeration, outward economy, and the degree of development of modern service industries on China's high-tech industries' innovation efficiency.

Government support (RS). In order to enhance the regional competitiveness of high-tech industries, China's provincial governments give different levels of support to these industries. The government uses public finance to support the innovation of high-tech industries, which contributes to an improvement in innovation efficiency. The proportion of R&D expenses in the GDP is used to measure a province's support to the innovation of high-tech industries.

R&D input intensity (II). Most high-tech industries are characterized by a high input and a high risk. The higher the R&D, the larger the R&D capital, which makes it easier to exert the scale effect of R&D capital and improve innovation efficiency. The proportion of R&D expense in the main business income can be used to measure the R&D input intensity of a province's high-tech industries.

Industries agglomeration (IA). Industries agglomeration results in the agglomeration of the innovation element. Most researchers hold the view that the agglomeration of the innovation element has a positive impact on the efficiency of technological innovation through a spillover effect and mutual "hitchhike" [41–43]. This paper selects an entropy index to measure high-tech industries agglomeration. Suppose that A is the total output of a certain province's high-tech industries sector, and A_i is the output of the high-tech industries of the i province. We then get $\sum_{i=1}^{N} A_i = A$, $P_i = A_i/A$ and $\sum_{i=1}^{N} P_i = 1$. The entropy index of high-tech industries agglomeration can be calculated by the formula $H = -\sum_{i=1}^{N} P_i \log P_i (H \geq 0)$. If $A_1 = A_2 = \cdots = A_n$, then $P_1 = P_2 = \cdots = P_n$, which means that the distribution of this province's high-tech industries area is in equilibrium, the professional level is the lowest, and H reaches the maxim value of $\log N$.

Outward economy (OE). Numerous research studies show that the higher the opening degree of an area, the greater the external trade and investment, and the greater the area's potential for technological innovation. This paper selects the proportion of foreign investment in the total investment as a main indicator of a province's economic openness.

Developed degree of modern service industries (SI). Modern service industries, such as finance, intermediary services, and information, are the foundation and guarantee of technological innovation. Developed modern service industries can effectively reduce the cost of high-tech industries innovation and improve the efficiency of technological innovation. This paper selects the proportion of modern service industries in the whole of service industries to measure the developed degree of modern service industries.

5.2. Model Assignment

From the viewpoint of Anselin [44], a certain area's economic characteristics are not isolated, but related to the characteristics of the adjacent areas—namely, distinct spatial correlation characteristics. If there is spatial heterogeneity or spatial correlation among the cross section data, then the linear regression model may deviate in the analysis of the correlation between the independent variables and the dependent variables. This paper considers that the spillover effect of innovation activities is evident, i.e., a province's high-tech industries' innovation efficiency does affect the surrounding provinces. Therefore, the spatial effect should be regarded as the premise of the analysis on the influencing factors of China's high-tech industries' innovation efficiency.

Spatial statistics use the spatial autocorrelation index *Moran's I* to test the existence of spatial correlations. This paper employs GEODA to test the spatial correlation of China's high-tech industries' innovation efficiency from 1999 to 2018. For most years, the normal statistics Z value of *Moran's I* exceeds the critical value of 5% (as shown in Table 2), which shows an obvious dependence the high-tech industries' innovation efficiency on their spatial distribution.

Table 2. High-tech industries' innovation efficiency.

Years	*Moran's I*	Critical Value Z(I)	Years	*Moran's I*	Critical Value Z(I)	Years	*Moran's I*	Critical Value Z(I)	Years	*Moran's I*	Critical Value Z(I)
1999	0.153	2.364	2004	0. 151	2.041	2009	0.152	2.946	2014	0.163	2.369
2000	0.167	2.632	2005	0.153	2.236	2010	0.154	1.871	2015	0.151	2.176
2001	0.131	2.145	2006	0.147	2.572	2011	0.138	1.945	2016	0.178	1.876
2002	0.136	2.041	2007	0.148	2.547	2012	0.143	2.394	2017	0.189	2.023
2003	0.135	1.902	2008	0.127	2.488	2013	0.153	2.531	2018	0.166	2.114

As a result of the spatial dependence of the high-tech industries' innovation efficiency, the traditional linear regression model may deviate when used to analyze the influencing factors of such innovation efficiency. Anselin pointed out two methods to solve spatial autocorrelation [44]. One is the Spatial Autoregressive Model (SAR), by adding weighting endogenous variables to the model;

the other is the Spatial Error Model (SEM), by adding spatial error terms to the model. This paper selects SAR to analyze the influencing factors of China's high-tech industries' innovation efficiency. The metering model is as follows:

$$E_{it} = \alpha_i + \beta_1 RS_{it} + \beta_2 II_{it} + \beta_3 IA_{it} + \beta_4 OE_{it} + \beta_5 SI_{it} + \rho w E_{it} + \varepsilon_{it} \tag{4}$$

Here, E represents efficiency; RS, II, IA, OE, and SI respectively represent government support, R&D input intensity, high-tech industries agglomeration, outward economy, and the developed degree of modern service industries; ρ is a spatial lag coefficient; and W is the spatial weight matrix.

China's high-tech industries' innovation efficiency includes technology development efficiency, technology conversion efficiency, and holistic innovation efficiency. To compare the effect of those influencing factors on these three kinds of efficiency, this paper presents a metering analysis of the relationship between the three kinds of efficiency and those influencing factors.

5.3. Analysis of Empirical Results

To make a comparison, this paper uses Ordinary Least Squares (OLS) and SAR to analyze the influencing factors of China's high-tech industries' innovation efficiency. Considering the regional individual differences and the possible deviations of the time factors in the results, we used the time and individual two-way fixed effect model to estimate the parameters while making the comparison. The results are as follows (Table 3).

Table 3. Estimated results of influencing factors of China's high-tech industries' innovation efficiency.

Model	Parameter	Technology Development Efficiency (E^1)	Technology Conversion Efficiency (E^2)	Holistic Innovation Efficiency (E)
	RS	0.325 **	0.224	0.203 *
	II	0.168 **	0.085 ***	0.137 *
	IA	0.233 **	0.132 *	0.184 *
OLS	OE	0.261	0.108 **	0.257 *
	SI	0.197 *	0.160 *	0.181 *
	R^2	0.816	0.837	0.852
	Log likelihood	−72.37	−50.31	−77.49
	RS	0.273 **	0.261	0.198
	II	0.148 ***	0.123	0.129 **
	IA	0.209 ***	0.128 **	0.171 ***
SAR	OE	0.106 *	0.150	0.139 *
	SI	0.183	0.235 ***	0.228 **
	ρ	0.113 **	0.108 ***	0.120 ***
	R^2	0.914	0.889	0.938
	Log likelihood	−85.08	−112.33	−79.47

Notes: * indicates significance under the level of 10%; ** indicates significance under the level of 5%; *** indicates significance under the level of 1%.

The estimated results of OLS and SAR show that the spatial metering model's goodness-of-fit with regard to technological development efficiency, technological conversion efficiency, and holistic innovation efficiency is superior to the OLS estimation, which demonstrates the spatial correlation of China's high-tech industries' innovation efficiency. The spatial auto-regression coefficients ρ of technological development efficiency, technological conversion, and holistic innovation efficiency are respectively 0.113, 0.108, and 0.120, all exceeding the significant level. It implies a positive spatial dependence on the innovation efficiency of the neighboring provinces' high-tech industries.

The estimated results of the influencing factors of the high-tech industries' innovation efficiency show that the influence of government support, R&D input intensity, and industries agglomeration on technological development efficiency passes the significance test, and the influence coefficients are respectively 0.273, 0.148, 0.209, and 0.106, while the developed degree of modern service industries does not pass the significance test. The influence of industries agglomeration and the developed

degree of modern service industries on technological conversion efficiency passes the significance test, and the influence coefficients are respectively 0.128 and 0.235, while other factors do not pass the significance test. The influence of R&D input intensity, industries agglomeration, outward economy, and the developed degree of modern service industries on holistic innovation efficiency passes the significance test, and the influence coefficients are respectively 0.129, 0.171, 0.139, and 0.228. Therefore, different factors differ in their impact on technological development efficiency, technological conversion efficiency, and holistic innovation efficiency, and government support effectively improves technological development efficiency, but do not lead to outstanding improvement in technological conversion efficiency or holistic innovation efficiency. The improvement of R&D input intensity helps accelerate technological development efficiency and holistic innovation efficiency, but not technological conversion efficiency. Industries agglomeration has an impact on three kinds of efficiency: the biggest on technological development efficiency and the smallest on technological conversion efficiency. Outward economy has a positive effect on technological development and holistic innovation efficiency, but is not conducive to technological conversion efficiency. The developed degree of modern service industries does not seem to affect technological development efficiency.

The empirical findings indicate that R&D input intensity, industries agglomeration, outward economy, and the developed degree of modern service industries can improve the high-tech industries' innovation efficiency and holistic innovation efficiency due to their influence on technological development and conversion. If we ignore the two-stage structure of the high-tech industries' innovation efficiency, we are unable to understand how these factors affect innovation efficiency through their impact on technological development and conversion, which is crucial to the promotion of holistic innovation efficiency.

6. Conclusions

This paper establishes a shared inputs two-stage network DEA model to estimate the technological development efficiency and the holistic innovation efficiency of high-tech industries in different Chinese provinces from 1999 to 2018, and analyzes the influencing factors of the innovation efficiency of the high-tech industries of these provinces with a spatial metering model. The results are as follows: (1) There is an apparent regional difference in the high-tech industries' technological development efficiency, technological conversion efficiency, and holistic innovation efficiency, and the three kinds of efficiency are remarkably higher in the developed provinces of the eastern coast than in the central and western provinces, which are poorer. (2) Judging from the comparison, technological development efficiency in backward provinces is much higher than holistic innovation efficiency, which is greater than technological conversion efficiency; in developed provinces, technological conversion efficiency is usually higher than holistic innovation efficiency, which is higher than technological development efficiency. (3) Government support can effectively promote technological development efficiency, but not technological conversion efficiency or holistic innovation efficiency; R&D input intensity helps accelerate technological development efficiency and holistic innovation efficiency, but is not outstanding in improving technological conversion efficiency. (4) Industries agglomeration has an impact on three kinds of efficiency: the biggest on technological development efficiency and the smallest on technological conversion efficiency. (5) Outward economy has a positive effect on technological development and holistic innovation efficiency, but is not conducive to technological conversion efficiency. (6) The developed degree of modern service industries does not seem to affect technological development efficiency.

Based on these conclusions, the Chinese government should support and encourage high-tech industrial innovation. Firstly, the promotion of high-tech industrial innovation, including technological development and conversion, is a complex course to take for any country. Therefore, to improve the high-tech industries' innovation efficiency, attention must be paid to technological development efficiency and technological conversion efficiency. For example, the high-tech industries' technological development efficiency in Shaanxi is at the front of national rankings, but holistic innovation efficiency

is not high due to a relatively low technological conversion efficiency. Secondly, China should help promote the technological strengths and technological spillover effects of the provinces whose high-tech industries have a higher innovation efficiency, such as Beijing, Shanghai, Guangdong, and Jiangsu, in order to help enhance the innovation efficiency of the surrounding and poorer provinces. Thirdly and finally, according to the differences in the three kinds of efficiency among all provinces, factors such as industries agglomeration, R&D input intensity, and outward economy should be taken into consideration when executing different policies.

We proposed some measures to mitigate regional differences, to be carried out by the Chinese government: regional governments should (1) continue to increase support for high-tech industries and promote guidance and coordination policies; (2) pay attention to R&D investment and human resource advantages, and promote the development of high technologies, to lay the foundation for sustainable development; (3) strengthen the flow of innovative resources between provinces, actively introduce advanced technologies, and achieve the integration and development of high technologies and complementary resources; (4) accelerate market-oriented reforms and institutional innovations in the central and western regions, promote regional technology diffusion, improve the efficiency of regional resource allocation, and gradually realize the convergence of innovation efficiency in various regions, thereby increasing the level of innovation efficiency in backward areas.

Appendix A

$$E = \max \frac{\sum\limits_{p=1}^{q} \omega_p^1 Z_{pk} + \sum\limits_{r=1}^{s} u_r Y_{rk} - u_k^1 - u_k^2}{\sum\limits_{i=1}^{m} v_i^1 \alpha_i X_{ik} + \sum\limits_{i=1}^{m} v_i^2 (1-\alpha_i) X_{ik} + \sum\limits_{p=1}^{q} \omega_p^2 Z_{pk}}$$

$$\text{Suppose that } t = \max \frac{1}{\sum\limits_{i=1}^{m} v_i^1 \alpha_i X_{ik} + \sum\limits_{i=1}^{m} v_i^2 (1-\alpha_i) X_{ik} + \sum\limits_{p=1}^{q} \omega_p^2 Z_{pk}}.$$

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