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Research Article

Research on the Technological Innovation Efficiency of China's Strategic Emerging Industries Based on SBM: NDEA Model and Big Data

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Characterized by large scale, variety, fast generation, and extremely high value but low density, big data can be used to mine effective information, provide users with auxiliary decision-making, and realize its own value. Based on the nonoriented SBM and the network DEA model, this paper systematically and objectively evaluates the technological innovation efficiency of strategic emerging industries in all provinces of China in 2002–2013. The study found the following. (1) The overall technological efficiency of China's strategic emerging industries is low. The average of comprehensive efficiency is 0.278; of 26 provinces, only 8 are above the average level. (2) The efficiency in the commercialization stage of scientific and technological achievements of strategic emerging industries in the whole country and most of the provinces is higher than that in the stage of knowledge innovation. The inefficiency of the knowledge innovation stage restricts the efficiency promotion of China's strategic emerging industries. (3) The overall innovation efficiency of strategic emerging industries has been increasing from 2002 to 2013. In comparison, the growth rate of pure technical efficiency is larger than that of scale efficiency. (4) The overall efficiency, the efficiency in the knowledge innovation stage, and the efficiency in the commercialization stage of scientific and technological achievements of the eastern region are higher than those of the central and western regions.

1. Introduction

After the international financial crisis in 2008, the world's major developed countries rerecognized the strategic significance of the real economy with the manufacturing industry as a mainstay, implemented the reindustrialization strategy, and pushed forward the development of strategic emerging industries with high technology, high risk, low carbon, and high research and development level to promote economic growth and achieve economic recovery. The strategic emerging industries have been regarded as the core industries to seize the commanding heights of the economy and the dominant force of a new round of international competition, and developing strategic emerging industries will certainly become the breakthrough for China's industrial structure optimization and upgrading and economic sustainable development. In recent years, the Chinese government has been attaching great importance to the development of strategic emerging industries. On October 18, 2010, the State Council issued the *Decision of the State Council on Accelerating the Fostering and Development of Strategic Emerging Industries*, formulated and proposed a series of plans to nurture and promote the development of strategic emerging industries, and defined seven major industrial areas: energy conservation and environmental protection, a new generation of information technology, new materials, new energy, biomedicine, high-end equipment manufacturing, and new energy automobiles. *Made in China 2025* issued by the State Council on May 20, 2015, clearly pointed out that through the government guidance

and integration of resources, five major projects including establishing a manufacturing innovation center, boosting intelligent manufacturing, strengthening industrial development at the grass-roots level, green manufacturing, and high-end equipment innovation, technological breakthroughs that constrains the development of manufacturing industries to enhance overall competitiveness of China's manufacturing and strategic emerging industries can be achieved. On December 19, 2016, the State Council published a *Guideline on Emerging Sectors of Strategic Importance During the 13th Five-Year Plan Period*, which adopted a comprehensive plan for development goals, key tasks, and policy measures of China's strategic emerging industries during the 13th five-year plan period. According to the guideline, by 2030, emerging sectors of strategic importance will become a leading force driving the sustained and healthy development of China's economy, China will become the world's important manufacturing center and innovation center of strategic emerging industries, and a number of innovative enterprises with global influence and leading role will spring up.

At present, China is the largest manufacturing economy in the world, and its manufacturing industry occupies a key position in the global manufacturing sector. Three economic regions, Yangtze River Delta, the Pearl River Delta, and Beijing-Tianjin-Hebei, have become competitive with industrial characteristics and the potential of becoming the world's leading industrial development base. However, the existing problem is that, in the labor system of international manufacturing sector, we have been lagging behind the global value chain controlled by the developed countries and in the low end of the global value chain for a long time [1, 2]. According to statistics, the average annual growth rate of R&D expenditure, full-time equivalent of research personnel, number of patent applications, and number of valid patents were 23.54%, 14.9%, 34.18%, and 40.13%, respectively, in 2012–2013, and the growth rate was the highest in the world, while the annual growth rate of sales of new products over the same period was 20.82%. This shows that China's patent application quantity and number of patents granted increased greatly, but at the same time many patents did not translate into the actual product sales. Therefore, compared with developed countries, the innovation efficiency of China's strategic emerging industries needs to be improved, especially the efficiency of transformation of scientific and technological achievements. Therefore, accurate and systematic assessment of the innovation efficiency of strategic innovation industries has important implications for optimizing the allocation of innovation resources, promoting strategic emerging industries to enhance the capacity of independent innovation and global value chain transitions, elevating domestic technical content of export products, and breaking the low-end lock of global value chain dilemma.

2. Literature Review

At present, there are two kinds of methods for evaluating the innovation efficiency of industries at home and abroad: one is the parametric method, which is mainly represented by stochastic frontier analysis (SFA); the other is nonparametric method, mainly represented by data envelopment analysis (DEA). In the study of innovation efficiency of strategic emerging industries, most scholars use DEA method. Raab et al. [3] used the input-oriented CCR model to evaluate the efficiency of high-tech industries in 50 states of the United States in 2002. Chen et al. [4] used the input-oriented CCR model to evaluate the comprehensive efficiency of six high-tech industries in Hsinchu Science Park, Taiwan, in 1991–1996. Lu et al. [5] used the DEA-Tobit model to evaluate the efficiency of 194 high-tech enterprises in Taiwan. Xiao and Xie [6] analyzed the influence of independent innovation, technology introduction, technological transformation, and digestive absorption on the innovation efficiency of China's strategic emerging industries and found that the independent innovation and technology introduction had significant impact on the innovation efficiency, and the impact of technological innovation and digestive absorption on innovation efficiency was not significant. Liu and Xia [7] estimated the innovation efficiency of 89 listed companies in 2007–2010 based on the SFA method and analyzed the influencing factors of innovation efficiency using the Tobit model. Li and Li [8] established stochastic frontier model (SFA) by using panel data of 10 Chinese LED listed companies in 2008–2010 as samples to calculate the innovation efficiency of LED strategic emerging industries and then put forward corresponding measures to improve innovation efficiency of China's emerging sectors. Lv and Sun [9] analyzed the technical efficiency and its influencing factors of the 19 categories of industries in China using SFA model. The results show that there are industrial heterogeneity and regional heterogeneity in the development of China's emerging industries. Huang and Zhang [10] adopted the Malmquist index decomposition method based on DEA model and estimated the Malmquist index of technical innovation in 28 provincial administrative regions and three major regions (eastern, central, and western regions) by using the provincial panel data of China in 2005–2012. Based on the index system in the Oslo manual, Zhang et al. [11] evaluated the innovation capacity of strategic emerging industries of 21 sample cities and explored the inherent evolution law and its application in the strategic emerging industries using gray fuzzy evaluation method and kernel density analysis. Liu et al. [12] adopted the DEA model to study the comprehensive efficiency, pure technical efficiency, and scale efficiency of China's strategic emerging industries using the panel data of 28 provinces and municipalities in China from 2007 to 2012. The results show that the pure technological efficiency of China's strategic emerging industries is at a low level, showing the process of rising first and then declining. Chen [13] used a three-stage DEA model to conduct a comparative study of its financing efficiency. The study found that the low financing efficiency of SMEs on the New Third Board was mainly affected by the low-scale efficiency caused by unreasonable input and output. Liu [14] measured the short-term and long-term innovation efficiency of five subsectors of strategic emerging

industries in Liaoning Province from 2000 to 2011 and discussed the impact of imitative innovation and independent innovation on innovation efficiency using DEA. Guo et al. [15] used the DEA model and the Malmquist index decomposition method to measure the technological efficiency, technological progress, and all factors in the process of high-tech industry innovation in 30 provincial administrative regions and three major regions (east, central, and western regions) of China's Productivity Growth and cluster analysis of regional high-tech innovation efficiency levels. It is found that, since 2009, the efficiency of technological innovation in China's regional high-tech industries has generally shown an upward trend, but it has been subject to large fluctuations. Zhang et al. [16] analyzed the achievements and efficiency of scientific and technological innovation in 31 provinces and cities of China and used the improved two-stage dynamic network DEA model to divide the innovation behavior of each region after the release of scientific and technological innovation policy into two stages. The first stage is from innovation input to intermediate innovation output stage, and the second stage is from intermediate output to achievement transformation stage, obtaining two-stage efficiency scores. Sun et al. [17] believed that there is a significant spatial correlation in the process of upgrading the urban industrial structure in China; the "U-shaped" relationship between the rationalization of the industrial structure and the urban total factor productivity; the performance between the advanced industrial structure and the urban total factor productivity out of the "inverted *U*" relationship. Han et al. [18] constructed a two-stage input-output index system of high-tech enterprise technology innovation based on the characteristics of high-tech enterprise technology innovation and considering the time lag effect, applied the dynamic two-stage DEA model to evaluate the performance of the two stages, and comprehensively analyzed the efficiency of high-tech enterprises in each province in the two stages of technology R&D and technology transformation. Zeng et al. [19] used the data envelopment analysis CCR model to calculate the comprehensive efficiency value under the condition of constant scale returns, and the BCC model calculates the pure technical efficiency value and the scale efficiency value under the conditions of variable scale returns. The efficiency is analyzed, and the trend of production efficiency is analyzed through the Malmquist model. Li et al. [20] used DEA model and Malmquist index decomposition method to measure the technological efficiency, technological progress, and total factor productivity growth in the process of high-tech industry innovation in 30 provincial administrative regions and three major regions of China by using the interprovincial R&D panel data of China's high-tech industry from 2009 to 2016 and made cluster analysis on the efficiency level of regional high-tech innovation. Guo and Li's [21] research believed that enterprise independent innovation and technology credit can have a significant positive impact on manufacturing innovation efficiency, and there are significant regional differences in the impact of technology finance on manufacturing innovation efficiency.

Based on research results of innovation efficiency of strategic emerging industries by domestic and foreign scholars, this paper argues that there are two shortcomings in the following two aspects. First, it focuses on the evaluation of single-stage innovation efficiency and the influencing factors. Most literatures mainly consider the innovation process of strategic emerging industries as a black box, regardless of internal structure and internal operating mechanism of the industrial innovation system. Second, when using DEA method to evaluate the innovation efficiency of strategic emerging industries, the traditional input- or output-oriented CCR and BCC models are mainly adopted, which ignore the information of slack variable; that is, the improvement is not reflected in the measurement of innovation efficiency value, which may cause a deviation in the efficiency measure. At the same time, the overall comparison of the efficiency of decision-making unit becomes more difficult when the input factor is increased and the slack output is considered. In order to make up for the shortcomings of the existing literature, this study divides the innovation system into the stage of knowledge innovation and the stage of commercialization of scientific and technological achievements. The regional differences and variation trends of innovation efficiency of China's strategic emerging industries are investigated using provincial panel data with network DEA (NDEA) model proposed by Tone et al. [22] and SBM model to accurately study innovation of strategic emerging industries and to provide references for regional innovation policy adjustment.

3. Two-Stage NDEA Model of Strategic Emerging Industries Based on SBM

3.1. Two-Stage Chain Process Division of Technological Innovation of Strategic Emerging Industries. The process of technological innovation is a process of transforming knowledge, skills, and materials into customer-satisfaction products. It is the evolution of knowledge generation, creation, and application. From the perspective of value chain, the process of enterprise technological innovation involves a series of value-added processes such as innovation resource input, innovation idea generation, research and development, technical management and organization, engineering design and manufacturing, user participation, and marketing. In the process of innovation, these value-added activities are interrelated and sometimes are operated in parallel. The entire technical innovation system is a community of the interaction between technology and economic activities. Specifically, in the process of technological innovation, once the new technology or technique is invented, new products and new more advanced production mode will be created through new technology, new process applications, and industrialization process to meet customer needs, so that the innovation resources are value-added. In the application of new technology, new technique, and industrialization process, the innovation system will timely transfer the customer's expectations, changes in demand, technical trends, and others to the development and application of new technologies and techniques through its

own feedback mechanism, thus promoting continuous improvement of technological innovation system.

Based on the above analysis, innovation output includes scientific and technological achievements and economic benefits based on the industry level. Scientific and technological achievements (technological output), as an intermediate output, are both the result of upfront innovation resource investment and the premise of later-stage new product development and technology improvement. Therefore, the process of technological innovation forms two innovative stages linked by technological output and input. The first stage is the stage of knowledge innovation from resource input to technological output, which produces intellectual output mainly through R&D funds and personnel input, etc., such as patented technology and non-patented technology; the second stage is the commercialization stage of scientific and technological achievements from the technical output to the economic benefits, which improve business sales income, especially the sales of new products, and then the economic benefits mainly through new product development and new technological transformation. The process of the two stages is shown in Figure 1.

3.2. Two-Stage DEA Model considering Slack Variables. Data envelopment analysis (DEA) is a method of empirically measuring productive efficiency of decision-making units (or DMUs) of multiple inputs and outputs introduced by Charnes et al. in [23]. SBM model is the DEA model based on the slack variable measurement proposed by Tone [24]. It belongs to the nonradial DEA model. Compared with the traditional radial DEA models, CCR and BCC models, SBM model also considers the slackness of input and output. The noneffective degree of DMUs is measured by the average proportion of input (output) reduction (increase). The DMUs in the model do not have to follow the ray direction proportionately, so SBM model can improve the input and output to the maximum extent, but SBM model still considers the DMUs as a black-box system in the process of efficiency evaluation, and the estimated efficiency value does not reflect the internal structure and operation mechanism of the evaluation object system. Fare and Grosskopf [25] have laid the foundation for the development of the network DEA model and constructed the network DEA framework model. The model shows two basic characteristics of the chain network system: first, it contains two or more subsystems; second, the subsystems are linked by intermediate variables. Since then, many scholars such as Lewis et al. [26], Kao and Hwang [27], and Tone and Tsutsui [22] improved models on the basis of the model. Among them, Tone and Tsutsui [22] proposed the network DEA model taking slacks into account, that is, SBM-NDEA (Slacks-Based Measure Network DEA) model, which effectively combines SBM model and the traditional network DEA model, ensuring the accuracy of the efficiency measurement. The SBM-NDEA model is expressed as follows.

Given n decision-making units DMUj ($j = 1, 2, ..., n$), each decision-making unit consists of K nodes, and m_k and r_k refer to the numbers of input indicators and output indicators, respectively; $X_j^k = (X_{1j}^k, X_{2j}^k, \ldots, X_{m_k j}^k)^T$ represents the input vector of the DMUi at node k, $Y_j^k = (Y_{1j}^k, Y_{2j}^k, \ldots, Y_{m_k j}^k)^T$ represents the output vector of the DMUi at node k, $Z_j^{(k,h)} = (Z_{1j}^{(k,h)}, Z_{2j}^{(k,h)}, \cdots, Z_{t(k,h)j}^{(k,h)})^T$ represents the middle vector of the DMUi from node k to node h, (k, h) indicates from node k to node h, t (k, h) represents the intermediate index number of (k, h), L stands for a collection of intermediate indicators, and the production possibility set of $\{(X^k, Y^k, Z^{(k,h)})\}$ under CRS is expressed as

$$\begin{aligned} X^k &\geq \sum_{j=1}^{n} X_j^k \lambda_j^k \quad (k = 1, \ldots, K), \\ Y^k &\leq \sum_{j=1}^{n} Y_j^k \lambda_j^k \quad (k = 1, \ldots, K), \\ Z^{(k,h)} &\geq \sum_{j=1}^{n} Z_j^{(k,h)} \lambda_j^{(k,h)} \quad (\text{as the output of } k), \\ Z^{(k,h)} &\geq \sum_{j=1}^{n} Z_j^{(k,h)} \lambda_j^{(k,h)} \quad (\text{as the input of } h). \end{aligned} \tag{1}$$

For VRS, add constraint condition $\sum_{j=1}^{n} \lambda_j^k = 1\,(\lambda_j^k \geq 0,\ k = 1, \ldots, K)$.

$\mathrm{DMU}_{jo}\,(j0 = 1, 2, \ldots, n)$, (X_o, Y_o) ,$s_0^{k-} = (s_{1o}^{k-}, s_{2o}^{k-}, \ldots, s_{m_k o}^{k-})^T$ represents the input slack vector of DMU_{jo} at node k, $s_o^{k+} = (s_{1o}^{k+}, s_{2o}^{k+}, \ldots, s_{m_k o}^{k+})^T$ corresponding input-output meets

$$\begin{aligned} x_o^k &= \sum_{j=1}^{n} x_j^k \lambda_j^k + s_o^{k-} \quad (k = 1, \ldots, K), \\ y_o^k &= \sum_{j=1}^{n} y_j^k \lambda_j^k - s_o^{k+} \quad (k = 1, \ldots, K), \\ s_o^{k-} &\geq 0, s_o^{k+} \geq 0, \lambda^k \geq 0 \quad (k = 1, \ldots, K). \end{aligned} \tag{2}$$

The intermediate index under slack network DEA model satisfies the following formula:

$$z_o^{f(k,h)} = \sum_{j=1}^{n} z_j^{f(k,h)} \lambda_j^k + s_o^{f(k,h)} \quad (k = 1, \ldots, K), \tag{3}$$

where $\sum_{j=1}^{n} z_j^{f(k,h)} \lambda_j^k = \sum_{j=1}^{n} z_j^{f(k,h)} \lambda_j^h$ indicates that the intermediate variable satisfies the output of the previous node equal to the input of the next node. $Z_j^{f(k,h)} = (Z_{1j}^{f(k,h)}, Z_{2j}^{f(k,h)}, \ldots, Z_{t(k,h)j}^{f(k,h)})^T\,(k = 1, \ldots, K)$ stands for free intermediate index, f (k, h) stands for free intermediate index number, and $s_o^{f(k,h)} = (s_{1o}^{f(k,h)}, s_{2o}^{f(k,h)}, \ldots, s_{t(k,h)}^{f(k,h)})^T$ indicates the slack vector of (k, h) free intermediate index and is unrestraint.

Definition 1. θ^* refers to overall efficiency of DMU_{jo}. When $\theta^* = 1$, DMU_{jo} is valid; when $\theta^* < 1$, DMU_{jo} is invalid. The overall efficiency of DMU_{jo} under different orientations is

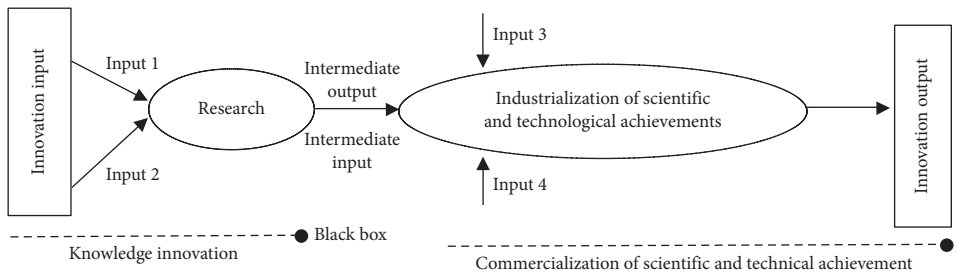

Figure 1: Value chain process of technical innovation activities in two stages.

$$\begin{aligned}
&\text{Input-oriented,} \quad \theta^* = \min_{\lambda^k, s^{k-}} \sum_{k=1}^{k} w^k \left[1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k}\right)\right],\\
&\text{Output-oriented,} \quad \theta^* = \min_{\lambda^k, s^{k+}} \frac{1}{\sum_{k=1}^{k} w^k \left[1 + 1/r_k\left(\sum_{r=1}^{r_k}\left(s_r^{k+}/y_{ro}^k\right)\right)\right]},\\
&\text{Non-oriented,} \quad \theta^* = \min_{\lambda^k, s^{k-}, s^{k+}} \frac{\sum_{k=1}^{k} w^k \left[1 - 1/m_k\left(\sum_{i=1}^{m_k}\left(s_i^{k-}/x_{io}^k\right)\right)\right]}{\sum_{k=1}^{k} w^k \left[1 + 1/r_k\left(\sum_{r=1}^{r_k}\left(s_r^{k+}/y_{ro}^k\right)\right)\right]},
\end{aligned} \tag{4}$$

where $1 - 1/m_k\left(\sum_{i=1}^{m_k} s_i^{k-}/x_{io}^k\right)$ indicates the average reduction rate of the DMU at node k; $\left[1 + 1/r_k\left(\sum_{r=1}^{r_k} s_r^{k+}/y_{ro}^k\right)\right]$ represents the average increase rate of node k, w^k 为 refers to the weight of node k, and $\sum_{k=1}^{k} w^k = 1$.

Definition 2. s_i^{k-*} and s_r^{k+*} are slacks of input and output, respectively, when the optimum efficiency is assigned for DMU_{jo} under different orientations, and θ^k refers to the efficiency of node k. Under different orientations, the efficiency of DMU_{jo} at node k is

$$\begin{aligned}
&\text{Input-oriented,} \quad \theta^k = 1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{io}^k}\right),\\
&\text{Output-oriented,} \quad \theta^k = \frac{1}{1 + 1/r_k\left(\sum_{r=1}^{r_k}\left(s_r^{k+*}/y_{ro}^k\right)\right)},\\
&\text{Nonoriented,} \quad \theta^k = \frac{1 - 1/m_k\left(\sum_{i=1}^{m_k}\left(s_i^{k-*}/x_{io}^k\right)\right)}{1 + 1/r_k\left(\sum_{r=1}^{r_k}\left(s_r^{k+*}/y_{ro}^k\right)\right)}.
\end{aligned} \tag{5}$$

When $\theta^k = 1$, DMU_{jo} is valid at node k; when $\theta^k < 1$, DMU_{jo} is invalid at node k.

As defined by Definitions 1 and 2, the necessary and sufficient conditions for the overall effectiveness of DMU_{jo} are that all nodes are valid.

3.3. Setting of Input and Output Indicators

3.3.1. Input and Output Indicators of Knowledge Innovation Stage. As the first stage of technological innovation activities, knowledge innovation refers to new knowledge and new technology developed mainly through R&D activities. From the perspective of input indicators, scholars usually choose R&D investment and R&D personnel investment. The R&D funds are expressed by R&D internal fund expenditure and development costs of new products; and R&D personnel are expressed by full-time equivalent of research personnel. Specifically, we use the R&D capital stock and the new product development capital stock index to replace the indicator. For the measurement of R&D capital stock, the perpetual inventory method is used. 2002 is intended to be the base period, the 2002 R&D stock is R&D internal expenditure of strategic emerging industries in 2002 divided by the depreciation rate and average growth rate of several years after the base period, that is, $k_{2002} = I_{2002}/(\delta + \varsigma)$, where I_{2002} is traffic data of R&D internal expenditure of China's strategic emerging industries, and δ refers to the depreciation rate. Referring to the results of most of the researches, the depreciation rate is set to be 15%; ζ refers to average growth rate of R&D internal expenditure of China's strategic emerging industries. Based on this, it is calculated using perpetual inventory method, that is, R&D stock in t year = R&D stock in t-1 year X (1–15%) + R&D traffic in t year.

In terms of output index, the output of knowledge innovation stage mainly presents as patent and nonpatented technology. Because the nonpatented technology is enterprise business secret and is difficult to be accurately measured, the patented technology is major consideration. The patent application quantity and effective patents are taken as two indicators to measure the output of the knowledge innovation phase, which is consistent with most of the studies.

3.3.2. Input and Output Indicators of Commercialization Stage of Scientific and Technological Achievements. The commercialization stage of scientific and technological achievements is the second stage of technological innovation. The main purpose of this stage is to transform the first-stage intellectual output into economic benefit. In terms of input indicators, we take technology, capital, and personnel into consideration. As the two stages of technological innovation are closely related, the technical input mainly comes from the first stage of output; the number of patent applications and the number of valid invention patents are both output of the first stage and input of the second stage, so they are the common intermediate variables of the two stages of technological innovation. In terms of capital, the capital expenditure of technological transformation is taken as the capital investment in the commercialization of scientific and technological achievements. In terms of personnel investment, in consideration of important role of scientific and

technical personnel in the application and popularization of new technologies, scientific and technical personnel are taken as personnel investment at this stage. In terms of output indicators, the output at this stage is mainly reflected in the economic benefits. Learning from the practice of Peng et al. [28], the new product sales revenue and exports are selected to reflect the results of technological innovation. See Table 1 for input-output assessment indicator system.

3.4. Sample and Data Selection. According to the *China National Economy Classification Codes* (GB/T4754-2012), strategic emerging sectors are divided into the following industries: chemical manufacturing; traditional Chinese medicinal materials, and Chinese patent medicine processing industry; biological products manufacturing; aircraft manufacturing and services; spacecraft manufacturing; communication equipment manufacturing; radar and corollary equipment manufacturing; radio and television equipment manufacturing; electronic components manufacturing; electronic device manufacturing; home audio-visual equipment manufacturing; other electronic equipment manufacturing; electronic computer manufacturing; office equipment manufacturing; medical equipment and device manufacturing; and instrumentation manufacturing industry.

This paper is based on the data of strategic emerging industries of 26 provinces (municipalities and autonomous regions in China), and data in Tibet, Xinjiang, Hainan, Inner Mongolia, Qinghai, Hong Kong, Macao, and Taiwan are missing and eliminated. During the period from 2002 to 2013, due to the hysteretic nature of the two stages of technological innovation, referring to the research results of Guan and Liu [29], the final lag period of R&D investment is set to be 2 years; that is, there are a one-year lag period between innovation resources investment and scientific and technological achievements and a one-year lag period of the commercialization of scientific and technological achievements. Therefore, a lag of one year is adopted. The first-stage innovation resource investment, intermediate output and input, the final output use data of year t, year t+1, and year t+2, respectively, that is, input and output data of technological innovation of the first stage, are from 2002–2011 and 2003–2012, and the input and output data of the second stage are from 2003–2012 and 2004–2013, respectively. All data are derived from the 2002–2014 *China Statistical Yearbook on Science and Technology*, *China Statistical Yearbook on High Technology Industry*, *China Statistical Yearbook*, and provincial statistical yearbook.

4. Analysis and Discussion of Empirical Results

Based on the SBM-NDEA model of Variable Return to Scale (VRS), this paper uses the software MaxDEA6.4 to analyze the technological innovation efficiency of the strategic emerging industries in 26 provinces in China in 2002–2003. The results are shown in Tables 2 and 3. Based on the results of innovation efficiency, this paper will analyze the overall technical efficiency characteristics of strategic emerging industries, the regional differences of innovation efficiency and the convergence analysis, and the two-stage technological innovation efficiency.

4.1. Feature Analysis of Technological Innovation Efficiency. Nationwide, the overall technological efficiency of China's strategic emerging industries is low, the average overall efficiency is 0.278, and the minimum is 0.041 (Heilongjiang). The top three provinces are Tianjin (0.878), Beijing (0.778), and Shanghai (0.716) successively. Of 26 provinces in the study, only 8 are better than average, accounting for 30.76%; most of the provinces' overall efficiency of innovation is lower than the national average, indicating that most of provinces' innovation-driven development level is still low and resource utilization in the process of innovation is low, and the phenomenon of wasting resources is very serious. Further research shows that the pure technical efficiency value of most provinces is smaller than the scale efficiency value; the former is 0.488, and the latter is 0.576, which shows that the improvement of technological innovation efficiency of China's strategic growth industries is mainly dependent on scale economic effects, and the contribution of pure technical efficiency is relatively small.

In terms of the efficiency of the two-stage innovation, the average overall efficiency value of the 26 provinces in the knowledge innovation stage is 0.247, and the efficiency value of 18 provinces is below the average efficiency value, accounting for 69.24%. The top three are Tianjin (0.757), Beijing (0.677), and Guangdong (0.588), and the efficiency value of 17 provinces of knowledge innovation is less than 0.2. This shows that, in the period of knowledge innovation, the overall efficiency of China strategic emerging industries is low, the waste of innovation resources is serious, and the gap between innovation resource allocation and cultivation of innovative talents is increasing. It has restricted the improvement of overall innovation efficiency of China's strategic innovation industries. At the commercialization stage of scientific and technological achievements, the average overall efficiency value of the 26 provinces in China is 0.435, 11 provinces of which are higher than the national average. The top three provinces are Tianjin (1), Jiangsu (0.934), and Shanghai (0.897); Heilongjiang (0.129) is the lowest. It is noteworthy that the efficiency of scientific and technological achievements of Tianjin in 2002–2013 is effective, much higher than other provinces. In general, the efficiency of the commercialization state of scientific and technological achievements is higher than the efficiency of the knowledge innovation stage. This may be due to the fact that the Chinese government has made a substantial investment in the innovation resources in recent years, and the number of patent applications increased significantly, but the number of effective invention patents is lower than the number of patent applications. In addition, with the implementation of China's innovation-driven strategy, some provinces, especially in the eastern region, have established specialized agencies serving transformation of sci-tech achievements drawing on the advanced experience of developed countries, which effectively promoted the

Table 1: Assessment indicator system of two-stage technological innovation efficiency of strategic emerging industries.

Initial innovation input (**X**)	Fund input	R&D internal expenditure: billion yuan (X_1^1) New product development expenditure: billion yuan (X_2^1)
	Personnel input	Full-time equivalent of R&D personnel: (X_3^1)
Technological output (**MY**)	Knowledge innovation	Patent application quantity: (Y_1^1 or X_1^2) Effective patent application: (Y_2^1 or X_2^2)
Innovation resource input (**MX**)	Technological commercialization	Expenditure on technological transformation: yuan (X_3^2) Number of scientific and technical personnel (X_4^2)
Final output (**Y**)	Economic benefits	Sales of new products: yuan (Y_1^2) Exports: yuan (Y_2^2)

X_i^1 and Y_i^1 refer to input and output indicators of knowledge innovation at note 1; similarly, X_i^2 and Y_i^2 refer to input and output indicators of commercialization of scientific and technological achievements at node 2. At the same time, because technological output is both the output index of the first stage and the input index of the second stage, it has two marks.

Table 2: Comparative analysis of average efficiency value of different regions in 2002–2013.

Regions	Overall efficiency			Knowledge innovation stage			Commercialization stage of scientific and technological achievements		
	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency
Anhui	0.141	0.239	0.508	0.155	0.233	0.556	0.327	0.592	0.597
Beijing	0.778	0.822	0.944	0.677	0.762	0.876	0.895	0.899	0.992
Chongqing	0.346	0.417	0.664	0.309	0.377	0.677	0.527	0.683	0.710
Fujian	0.451	0.516	0.882	0.395	0.486	0.824	0.862	0.878	0.977
Gansu	0.081	0.632	0.128	0.081	0.647	0.128	0.208	0.929	0.249
Guangdong	0.644	1.000	0.644	0.588	1.000	0.588	0.735	1.000	0.735
Guangxi	0.162	0.618	0.225	0.146	0.612	0.198	0.241	0.814	0.279
Guizhou	0.077	0.267	0.295	0.065	0.259	0.349	0.141	0.337	0.392
Hebei	0.096	0.179	0.485	0.091	0.154	0.506	0.205	0.425	0.529
Henan	0.201	0.272	0.636	0.191	0.277	0.624	0.327	0.440	0.676
Heilongjiang	0.041	0.127	0.296	0.033	0.087	0.355	0.129	0.419	0.345
Hubei	0.143	0.191	0.674	0.128	0.159	0.704	0.256	0.335	0.729
Hunan	0.173	0.273	0.563	0.172	0.248	0.595	0.283	0.481	0.612
Jilin	0.129	0.338	0.329	0.133	0.323	0.376	0.204	0.492	0.381
Jiangsu	0.527	0.894	0.604	0.418	0.804	0.563	0.934	1.000	0.934
Jiangxi	0.108	0.174	0.553	0.108	0.162	0.583	0.295	0.482	0.605
Liaoning	0.197	0.244	0.793	0.154	0.175	0.862	0.469	0.541	0.855
Ningxia	0.114	0.990	0.114	0.115	0.988	0.115	0.318	1.000	0.318
Shangdong	0.261	0.294	0.902	0.239	0.285	0.834	0.495	0.528	0.952
Shanxi	0.389	0.991	0.394	0.389	1.000	0.389	0.465	0.991	0.470
Shaanxi	0.058	0.082	0.685	0.057	0.067	0.762	0.201	0.248	0.794
Shanghai	0.716	0.907	0.791	0.547	0.815	0.689	0.897	1.000	0.897
Sichuan	0.176	0.208	0.847	0.155	0.195	0.818	0.442	0.465	0.948
Tianjin	0.878	0.912	0.963	0.757	0.825	0.912	1.000	1.000	1.000
Yunnan	0.165	0.895	0.186	0.176	0.889	0.197	0.156	0.877	0.181
Zhejiang	0.168	0.194	0.868	0.150	0.183	0.816	0.298	0.308	0.972
Average	0.278	0.488	0.576	0.247	0.462	0.573	0.435	0.660	0.659

commercialization of scientific and technological achievements.

Table 3 shows the results of technological innovation efficiency of the strategic growth industries in 2002–2003. It can be seen from Table 3 that the overall innovation efficiency of strategic emerging industries has been on the rise from 2002 to 2013, increasing from 0.194 in 2002 to 0.311 in 2011, and reached the highest value of 0.436 in 2010. In contrast, the growth rate of pure technical efficiency is greater than that of scale efficiency, which shows that the development of China's strategic emerging industries has gradually evolved from the traditional low-end development relying on scale advantages to integrate into global value chain, and then embed in global value chain, ultimately leading to the development of global value chain, and the technical level of strategic emerging industries has been greatly improved. The overall efficiency of the knowledge innovation phase is greater than the commercialization stage of scientific and technological achievements, which depends largely on the rapid growth of pure technical efficiency in the knowledge innovation phase. The efficiency value of the overall efficiency, the knowledge innovation stage, or the

Table 3: Comparative analysis of average innovation efficiency in 2002–2013.

Year	Overall efficiency			Knowledge innovation stage			Commercialization stage of scientific and technological achievements		
	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency
2002–2004	0.194	0.394	0.510	0.168	0.379	0.515	0.405	0.660	0.584
2003–2005	0.179	0.417	0.452	0.151	0.387	0.428	0.374	0.620	0.633
2004–2006	0.191	0.417	0.458	0.131	0.375	0.409	0.337	0.573	0.564
2005–2007	0.172	0.416	0.453	0.163	0.424	0.461	0.296	0.652	0.458
2006–2008	0.248	0.457	0.543	0.185	0.417	0.430	0.384	0.734	0.526
2007–2009	0.314	0.523	0.614	0.312	0.480	0.732	0.507	0.698	0.738
2008–2010	0.313	0.512	0.660	0.327	0.525	0.724	0.460	0.627	0.762
2009–2011	0.419	0.585	0.736	0.389	0.562	0.739	0.613	0.715	0.853
2010–2012	0.436	0.602	0.746	0.393	0.569	0.743	0.594	0.738	0.804
2011–2013	0.311	0.553	0.586	0.252	0.500	0.547	0.380	0.584	0.664

commercialization stage of scientific and technological achievements decreased sharply after 2011. It may be related to the sluggish recovery of world economy after international financial crisis and implementation of the "reindustrialization" strategy by the developed countries.

4.2. Regional Difference and Convergence Analysis of Technological Innovation Efficiency. In order to examine the differences in innovation efficiency among regions, 26 provinces in China are divided into three regions: the eastern provinces include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong; the central region includes 8 provinces: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hubei, and Hunan provinces; and the western region includes Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, and Ningxia. From the results of innovation efficiency in subregions of Table 4, there is a large gap among the overall efficiency and efficiency in the knowledge innovation stage and the commercialization stage of scientific and technological achievements in the eastern, central, and western regions. The overall efficiency and efficiency in the knowledge innovation stage and the commercialization stage of scientific and technological achievements in the eastern region are higher than those of the central and western regions, indicating that the eastern region occupies the high-end segments of the domestic value chain, while the central and western regions are still in the low-end position. In both stages of knowledge innovation and the transformation of scientific and technological achievements, the pure technical efficiency in the western region is higher than that in the central region, which mainly benefited from continuous advancement of the western development strategy. The strategic emerging industries in the eastern region have been transferred to the western region, which has driven up the technological level of the entire western region. However, the scale efficiency of the western region in the stages of knowledge innovation and the transformation of scientific and technological achievements is lower than those in the eastern and central regions, which indicates that the scale effect of the strategic emerging industries in the western region has not yet appeared and the scale of industrial development should be further expanded. Chinese government should increase input in strategic emerging industries and constantly enhance the status of the industries in the domestic value chain. The central region should increase the use of innovation resources to reduce the waste of innovation resources, integrate more into the domestic value chain and the global value chain, and continuously upgrade the level of technological development of industrial sectors.

In order to further examine the variation trend of innovation efficiency gap, a convergence test is carried out. According to Barro et al. [30], convergence includes σ-convergence and β-convergence, and β-convergence includes absolute β-convergence and conditional β-convergence. σ-convergence means that the dispersion of real per capita income tends to decline over time, and β-convergence means that poor economies grow faster than rich economies. If the per capita income or output of each economy can achieve exactly the same steady-state level, it is absolute β-convergence, but if each economy approaches different steady-state level, it should be conditional β-convergence. We only take σ-convergence as an example in this paper. σ-convergence generally reflects the variation trend of the gap through the standard deviation or variable coefficient of national or regional level. Figure 2 gives variable coefficients of SBM innovation efficiency. It can be seen from Figure 2 that the variable coefficient of the innovation efficiency of strategic emerging industries among the provinces shows a significant downward trend, whether it is the overall efficiency, efficiency value of the knowledge innovation stage, or efficiency value of the transformation stage of the scientific and technological achievements. It indicates that σ-convergence exists and the gap of innovation efficiency among provinces is gradually narrowing. This also reflects the fact that, with the acceleration of international economic integration and regional economic integration, strategic emerging industries of the world and eastern regions have shifted to the central and western regions, and interregional economic activities and innovation activities have been more closely linked. The positive overflow effect of innovation

Table 4: Comparison of technological innovation efficiency value of strategic emerging industries in different regions.

Regions	Overall efficiency			Knowledge innovation stage			Commercialization stage of scientific and technological achievements		
	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency
Central region	0.472	0.596	0.788	0.402	0.549	0.747	0.679	0.758	0.884
Eastern region	0.166	0.326	0.494	0.164	0.311	0.523	0.286	0.529	0.552
Western region	0.147	0.514	0.393	0.138	0.504	0.406	0.279	0.669	0.484
National average	0.278	0.488	0.576	0.247	0.462	0.573	0.435	0.660	0.659

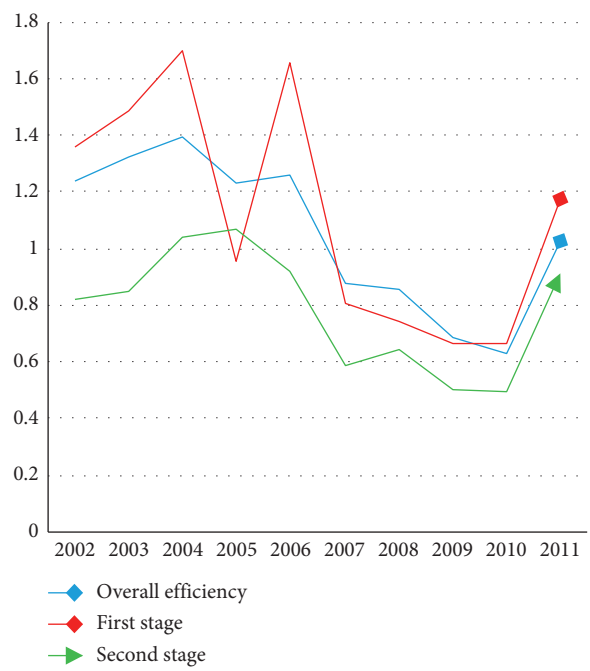

Figure 2: Variable coefficient trend of innovation efficiency of strategic emerging industries in 2002–2011.

activities among provinces is becoming more and more obvious. The central and western regions are improving technical level of strategic emerging industries by opening wider to the outside world, optimizing the industrial innovation environment, and introducing and absorbing advanced technologies.

4.3. Analysis of Technological Innovation Efficiency in Two Stages. In terms of innovation performance of strategic emerging industries in different stages, 26 provinces can be divided into four areas based on average efficiency. Class *A* area is an area of highly efficient and intensive technological innovation, which is mainly characterized by high efficiency of knowledge innovation and transformation of high-tech achievements. Such area boasts high level of economic development with good innovation environment and certain policy advantages and thus attracts high-end innovation

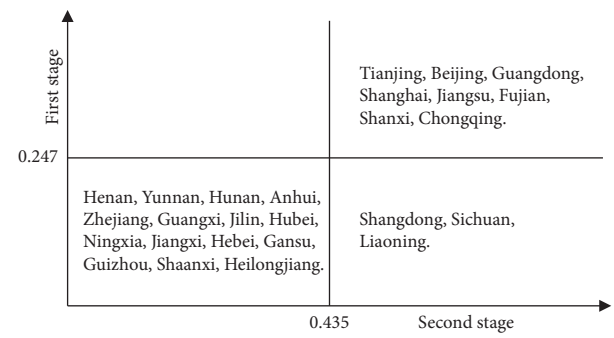

Figure 3: Distribution diagram of technical efficiency in two stages of provinces and cities in 2002–2013.

resources and elements. Industries in this area are at medium and high positions of the domestic value chain or global value chain. Class *B* area is characterized by high efficiency of knowledge innovation and low efficiency of transformation of high-tech achievements. This region has abundant innovative talents, but lacks effective industrial base and market environment. Class *C* area is characterized by low innovation efficiency and high efficiency of transformation of high-tech achievements, which is difficult to attract high-end innovation elements due to restricts of innovation environment, innovation policies, and industrial base, leading to inefficient knowledge innovation. Class *D* area is featured by extensive growth and inefficient technological innovation, which is characterized by low knowledge innovation efficiency and inefficient transformation of scientific and technological achievements. The innovation resource allocation is inefficient, and it also lacks good environment for innovation and commercialization of scientific and technological achievements in this area. Its industries are also at the lowermost position of domestic value chain and the global value chain. As shown in Figure 3, Class *A* area mainly consists of Tianjin, Beijing, Guangdong, Shanghai, Jiangsu, Fujian, Shanxi, and Chongqing, and most of these areas belong to the eastern developed regions; and no provinces belong to the Class *B* area, which demonstrates that basic research and innovation ability of China's strategic emerging industries is weak but also shows a more serious polarization phenomenon; area *C* consists of Shandong,

Sichuan, and Liaoning provinces, and the remaining provinces belong to Class *D* area. It indicates that the strategic emerging industries of the majority of China's provinces are still at the low end of the domestic value chain and global value chain with extensive industrial development model, and the competitiveness needs to be improved.

5. Conclusions and Suggestions

This paper divides the technological innovation process of strategic emerging industries into knowledge innovation stage and commercialization stage of scientific and technological achievements. Based on the nonoriented SBM model and the network DEA model, this paper systematically and objectively evaluates the technological innovation efficiency of strategic emerging industries in all provinces of China in 2002–2013. The study found the following. (1) The overall technological efficiency of China's strategic emerging industries is low. The average of comprehensive efficiency is 0.278 and the minimum is 0.041 (Heilongjiang). The top three provinces are Tianjin, Beijing, and Shanghai. Of 26 provinces in the study, only 8 are better than average, accounting for 30.76%. (2) From the efficiency estimation results of the two-stage innovation, the efficiency in the commercialization stage of scientific and technological achievements of strategic emerging industries in the whole country and most of the provinces is higher than that in the stage of knowledge innovation. This shows that, in the period of knowledge innovation, the overall efficiency of China strategic emerging industries is low, the waste of innovation resources is serious, and the gap between innovation resource allocation and cultivation of innovative talents is increasing. It has restricted the improvement of overall innovation efficiency of China's strategic innovation industries. (3) By stages, the overall innovation efficiency of strategic emerging industries has been increasing from 2002 to 2013. In comparison, the growth rate of pure technical efficiency is larger than that of scale efficiency. (4) Throughout the region, the overall efficiency, the efficiency in the knowledge innovation stage, and the efficiency in the commercialization stage of scientific and technological achievements of the eastern region are higher than those of the central and western regions. The variable coefficient of the innovation efficiency of strategic emerging industries among the provinces shows a significant downward trend.

Based on the above research conclusions, this article puts forward the following policy recommendations. (1) To improve the efficiency of technological innovation in strategic emerging industries, we should focus on advantageous resources. From the perspective of the cost-benefit ratio of resources, we should rationally design resource allocation, improve resource use efficiency, and comprehensively promote diffusion and transformation of technological innovations. (2) Strengthening cross-provincial horizontal communication and cooperation and the establishment of interprovincial information and resource exchange and interoperability platforms all contribute to the promotion of innovative activities and innovative exchanges between provinces and cities, which is fundamental to solve the problem of insufficient intermediate output sexual measures. (3) Focus on the promotion of superior experience and promote balanced development between regions. Comprehensively promote the experience of policy support, development concepts, technology development, and production models in advantageous regions. Through technical cooperation, experience dissemination, industrial alliances, personnel training, etc., promote the development of regions with low technological innovation efficiency and comprehensively enhance China's high technology. (4) The succession among policies should be strengthened, so that the latter policies become the booster of the previous policies, and then the performance of China's regional science and technology innovation policies should be improved.

Data Availability

The data used to support the results of this study have copyright issues and so cannot be made freely available. Requests for access to these data should be made to Zuchang Zhong, zhongzuc@163.com.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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