Research on Technological Innovation Efficiency of China's High-Tech Industry Based on Network SBM Model and DEA Window Analysis

Jian-li Chen and Ling-jie Meng

Abstract The paper combines network SBM model with DEA window analysis to measure the technological innovation efficiency of China's high-tech industry during 2000–2011. The research indicates that the overall efficiency of technological innovation of the high-tech industry shows a rising trend in the past 10 years, and the outbreak of the financial crisis has a negative impact on the efficiency of technological innovation in the short term. The efficiency values of technological innovation are still not high, and there is structural imbalance between R&D efficiency and conversion efficiency in the long term. The difference of the conversion efficiency among the industry segments shows trend of convergence, but the difference of R&D efficiency expands after the financial crisis.

Keywords DEA window analysis • High-tech industry • Network SBM model • Technological innovation efficiency

1 Introduction

The high-tech industry is a strategic leading industry in China, which has experienced rapid development in the past 10 years. The international financial crisis which broke out in 2008 once brought significant impact to the development

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of China's high-tech industry because of its high degree of internationalization. Therefore, it is of great significance for deepening the study of technological innovation efficiency by using advanced models and tools to measure the time trend and industrial difference in China's high-tech industry, especially reveal the impact of financial crisis on efficiency change.

In recent years, DEA method, particularly network DEA method becomes an important method at the forefront of the research of technological innovation efficiency. Using network DEA method, the technological innovation process can be decomposed to technological R&D process and technological conversion process, therefore it overcomes the shortcoming of the traditional DEA method which ignores internal production structure and thus cannot effectively estimate the real input-output efficiency. The easiest form of network DEA model is two-stage DEA model proposed by Sexton and Lewis (2003) [1], which treated technological R&D process and technological conversion process as independent units. Xiao, Feng and Han (2012) [2], Yu (2009) [3], Liu and Chen (2011) [4] all have used this method to study the two stage efficiencies of China's high-tech industry. The two-stage DEA model does not consider the correlation between the stages, and cannot estimate the overall efficiency in a unified framework. In recent years, the relational network DEA models have been gradually applied in evaluating the technological innovation efficiency in China's high-tech industry. Chen, Feng, Jiang and Kang (2010) [5], Qian, Chen and Xiao (2012) [6] all used chain relational network DEA model to evaluate the overall efficiency and divisional efficiency of China's regional innovation of the high-tech industry. Yin (2012) [7] utilized network SBM model to measure efficiency of regional innovation in China. Feng, Ma and Zhang (2011) [8] evaluated the industrial innovation efficiency of high-tech industry by using chain network DEA model.

Currently, scholars mostly use cross-sectional data to estimate the technological innovation efficiency of China's high-tech industry by using network DEA model, their research results are thus confined in the latest technological innovation period. This paper attempts to combine network SBM model with DEA window analysis to measure the dynamic trend of the technological innovation efficiency based on the panel data of China's high-tech industry during 2000–2011.

2 Methodology

2.1 Research Methods

There are various forms of DEA model from different perspectives [9–12]. Network SBM model proposed by Tone and Tsutsui (2009) [13] cannot only estimate the overall efficiency of a network DMU, but also decompose the overall efficiency into divisional efficiencies. It is a non-radial DEA model, and can set the right weight based on the importance of various divisions.

This paper utilizes the input-oriented SBM model under the assumption of variable returns-to-scale (VRS) and free link case. Consider a system of two processes. Let $x_{ij}^k (i = 1, 2, \ldots, m_k)$ and $y_{rj}^k (r = 1, 2, \ldots, r_k)$ be defined as the inputs and outputs to $DMU_j (j = 1, 2, \ldots, n)$ at process $k (k = 1, 2)$. Denote $z_{dj} (d = 1, 2, \ldots, t)$ as the linking intermediate product from process 1 to process 2. The overall efficiency of DMU_0 is calculated by the following model:

$$\rho_0^* = \min_{\lambda^k, s^{k-}} \sum_{k=1}^{2} w^k \left[1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{i0}^k} \right) \right]$$

$$s, t. x_{i0}^k = \sum_{j=1}^{n} x_{ij}^k \lambda_j^k + s_i^{k-} \; (i = 1, 2, \ldots, m_k)$$

$$y_{r0}^k = \sum_{j=1}^{n} y_{rj}^k \lambda_j^k - s_r^{k+} \; (r = 1, 2, \ldots, r_k)$$

$$\sum_{j=1}^{n} \lambda_j^k = 1$$

$$\sum_{j=1}^{n} z_{dj} \lambda_j^1 = \sum_{j=1}^{n} z_{dj} \lambda_j^2, (d = 1, 2, \ldots, t)$$

$$\lambda_j^k \geq 0, s_i^{k-} \geq 0, s_r^{k+} \geq 0, w_k \geq 0, \sum_{k=1}^{2} w_k = 1, \forall k = 1, 2$$

Where ρ_0^* denotes the overall efficiency of DMU_0; s_i^{k-} and s_r^{k+} are input and output slacks of process k. w_k is the relative weight of process k. We put $w_1 = w_2 = 0.5$ in this article.

Let $\lambda_j^{k*}, s_i^{k-*}, s_r^{k+*}$ denote the optimal solution solved form the above model. Then the overall efficiency and the efficiency of process k can be calculated as:

$$\rho_0^* = \sum_{k=1}^{2} w_k \left[1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{i0}^k} \right) \right]$$

$$\rho_k^* = 1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{i0}^k} \right), \quad k = 1, 2$$

Network SBM model can only analyze cross-sectional data, which means that the role of the time cannot be considered. In this paper, we use panel data of China's high-tech industry from 2000 to 2011, and try to combine network SBM model and DEA window analysis proposed by G. Klopp (1985) [14] to estimate the efficiency. In other words, we use network SBM model to estimate all DMU's efficiencies in each window. DEA window analysis treats the DMUs of different time as different DMU, and selects a different reference set to evaluate the relative efficiency of a DMU by using the method similar to the moving average [15]. Therefore, the efficiency values evaluated by this method cannot only reflect the heterogeneity between each DMU, but also reflect the changes of each DMU's efficiency [16].

2.2 Input/Output Indicator Selection

The process of technological innovation has apparent characteristics of two-stage. The first stage is the process of the technology research and development. In this stage, R&D departments product patents, papers, monographs and the others outputs with the R&D investments. The second stage is the conversion of the technological achievements, which includes the industrialization of domestic technological innovations and the foreign technology from acquisition. The above structure of the technological innovation is a simplified form of the network structure.

We choose intramural expenditure on R&D and full-time equivalent of R&D personnel as the inputs of technology R&D stage, and the number of patent applications as the output. Considering the impact of R&D activities on the production of knowledge is a continuous process, we utilize R&D capital stock which is calculated by using the perpetual inventory method instead of using the intramural expenditure on R&D directly. The intramural expenditure on R&D should be deflated by the R&D price index [4] before calculating R&D capital stock, in which the R&D price index = 75 %*PPI + 25 %*CPI.

The inputs of the technological conversion process include the output of the first stage, number of patents in force, expenditure on new products development, expenditure on technology acquisition and reconstruction, and annual average number of employed personnel. We choose output value of new products, the sale rate of new products (sales revenue of new products/output value of new products), the export rate of new products (export sales revenue of new products/sales revenue of new products) as the outputs. In addition, the output value of new products should be deflated in order to eliminate the impact of price change. Industries in Manufacture of Medicines are deflated by PPI of the chemical industry and the other industries are deflated by PPI of the mechanical industry.

3 Empirical Results and Analysis

3.1 The Sample and Data

The sample of this study is the industry segments of China's high-tech industry, including Manufacture of Chemical Medicine (H1), Manufacture of Finished

Traditional Chinese Herbal Medicine (H2), Manufacture of Biological and Biochemical Chemical Products (H3), Manufacture and Repairing of Airplanes (H4), Manufacture of Spacecrafts (H5), Manufacture of Communication Equipment (H6), Manufacture of Radar and Its Fittings (H7), Manufacture of Broadcasting and TV Equipment (H8), Manufacture of Electronic Appliances (H9), Manufacture of Electronic Components (H10), Manufacture of Domestic TV Set and Radio Receiver (H11), Manufacture of Other Electronic Equipment (H12), Manufacture of Entired Computer (H13), Manufacture of Computer Peripheral Equipment (H14), Manufacture of Office Equipment (H15), Manufacture of Medical Equipment and Appliances (H16), Manufacture of Measuring Instrument (H17). The time period is from 2000 to 2011. Data for input and output are extracted from China Statistics Yearbook On High Technology Industry, and the other data are extracted from Wind Information. Considering the time delay between input and output, this study set a time lag of 1 year on input and output. Therefore, the input data of the technological R&D process are from 2000 to 2009,the output data of it are from 2001 to 2010,and the input data of the technological conversion process are from 2001 to 2010,the output of it are data from 2002 to 2011.

3.2 Results and Discussion

In this section, we apply the proposed method to estimate the overall efficiency, R&D efficiency and conversion efficiency of the 17 industry segments. The width of the window is set to be four. Calculation of the model is done through software DEA-Solver8.0.

We calculated the average efficiency of 17 industry segments in every year. Results presented in Fig. 1 show that the overall efficiency, the R&D efficiency and the conversion efficiency of china's high-tech industry all show a rising trend in the past 10 years, and the conversion efficiency is significantly higher than the R&D efficiency. The values of the three types of efficiency are all not high. Although the overall efficiency grows with an average annual rate of 4.42 %, its mean value is still lower than 0.5. The values of R&D efficiency are in the low growth range of 0.25–0.31. Therefore, the conversion efficiency has been the main driving force of the technological innovation efficiency of China's high-tech industry. Although the overall efficiency is in the rise, but there is a serious imbalance between R&D efficiency and conversion efficiency, which reveal that most of the high-tech industries in china have paid more attention to the conversion and application of technology than the technological R&D.

Since 2008, the conversion of the economic cycle and the impact of the financial crisis have brought significant influence on the efficiency change of technological innovation of China's high-tech industry. The biggest decline took place in 2009 from the perspective of efficiency trend. The overall efficiency fell 10.46 %, and R&D efficiency fell 13.97 % in 2009. But then, three types of efficiency values quickly rebounded, and the overall efficiency and the conversion efficiency reached

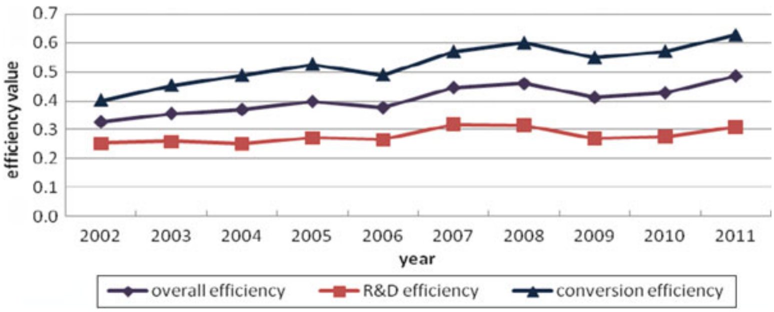

Fig. 1 Mean values of technological innovation efficiency for the 17 industry segments, 2002–2011

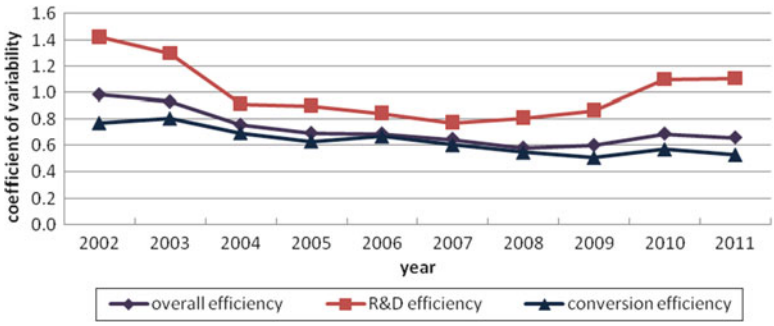

Fig. 2 The CV of technological innovation efficiency for the 17 industry segments, 2002–2011

a record high value. In practice, China's high-tech industries have showed the ability to return to growth and ability to withstand the crisis in the whole manufacturing industry. The financial crisis prompted more high-tech companies that rely on low-cost to pay more importance on technological innovation with upgrading the technological level and improving the efficiency of R&D and technological conversion.

We also calculate the coefficient of variability (CV) of efficiencies of 17 industry segments in every year. Results presented in Fig. 2 show that the CV of the overall efficiency and the conversion efficiency are both shrinking continually, but the CV of the R&D efficiency is increasing after 2007. These means that the difference of the degree of emphasis on R&D and independent innovation in China's high-tech industry is becoming bigger and bigger. It is no doubt that the comparative advantage in R&D efficiency will be helpful to the industry transformation and upgrading.

In order to thoroughly examine the impact of the financial crisis on the efficiency of technological innovation of China's high-tech industry, we calculate the average efficiency of 17 industry segments in three certain time intervals, that is interval I (2002–2011), interval II (2006–2008) and interval III (2009–2011). As can be seen

Table 1 Average efficiencies of 17 industry segments of Chinese high-tech industry in three intervals

	Interval I			Interval II			Interval III		
Industry	ρ_0^*	ρ_1^*	ρ_2^*	ρ_0^*	ρ_1^*	ρ_2^*	ρ_0^*	ρ_1^*	ρ_2^*
H1	0.104	0.049	0.158	0.102	0.055	0.148	0.144	0.070	0.217
H2	0.121	0.083	0.159	0.124	0.091	0.156	0.162	0.095	0.229
H3	0.331	0.228	0.434	0.364	0.282	0.447	0.403	0.243	0.563
H4	0.123	0.035	0.212	0.128	0.038	0.217	0.125	0.049	0.201
H5	0.560	0.303	0.817	0.649	0.361	0.937	0.555	0.214	0.896
H6	0.617	0.495	0.739	0.635	0.536	0.735	0.915	0.847	0.984
H7	0.547	0.345	0.748	0.685	0.437	0.933	0.585	0.361	0.808
H8	0.815	0.739	0.891	0.710	0.622	0.798	0.857	0.773	0.940
H9	0.174	0.081	0.267	0.168	0.088	0.248	0.188	0.080	0.297
H10	0.122	0.067	0.177	0.119	0.075	0.162	0.171	0.082	0.260
H11	0.397	0.238	0.556	0.373	0.220	0.527	0.299	0.124	0.474
H12	0.432	0.316	0.548	0.569	0.470	0.668	0.393	0.285	0.501
H13	0.624	0.371	0.877	0.620	0.297	0.943	0.586	0.336	0.836
H14	0.668	0.423	0.913	0.685	0.436	0.916	0.534	0.156	0.761
H15	0.795	0.680	0.911	0.750	0.648	0.851	0.817	0.706	0.928
H16	0.353	0.295	0.411	0.416	0.347	0.485	0.341	0.221	0.461
H17	0.158	0.081	0.234	0.161	0.095	0.228	0.214	0.101	0.326
Mean	0.408	0.284	0.532	0.427	0.300	0.553	0.429	0.279	0.570

Notes: ρ_0^* is overall efficiency; ρ_1^* is R&D efficiency; ρ_2^* is conversion efficiency

in Table 1, the average values of the overall efficiency and conversion efficiency in interval III are higher than those in interval I and interval II, but it not right to the R&D efficiency. This shows that the occurrence of the international financial crisis makes Chinese high technology enterprises pay more attention to the promotion of the conversion efficiency than the R&D efficiency which reflect the industry's core competitiveness. In fact, the expenditure for technical renovation and acquisition of foreign technology are significantly greater than the expenditure for assimilation of technology in China's high-tech industry for a long time. Most of the high-tech enterprises are keen on following foreign technology and expanding the production capacity at the low end of the value chain, which greatly inhibits the ability of independent innovation.

Conversion efficiency of all industries is higher than the R&D efficiency within the three intervals, which further indicates that the level of the two types of efficiency of China's high-tech industry is unbalanced. In the market-oriented and competitive environment, conversion efficiency tends to be slightly higher than R&D efficiency, which is reasonable normally. However, there may be problems in the development and transformation of the industry with the continuation of this situation. The prevalence of this problem also reflects the tendency of pragmatism in many high-tech industries, as well as the disjunction between the technological R&D and conversion. With the change of the international division of labor after the outbreak of financial crisis, lack of capability and efficiency for independent innovation will have a negative influence on international competitiveness and industrial upgrading of China's high-tech industry.

As can be seen from Table 1, both in the pre-crisis and post-crisis, the two types of efficiency values of Manufacture of Communication Equipment (H6), Manufacture of Broadcasting and TV Equipment (H8), Manufacture of Office Equipment (H15) have remained the leading. However, the two types of efficiency values are relatively lower in Manufacture of Chemical Medicine (H1), Manufacture of Finished Traditional Chinese Herbal Medicine (H2), Manufacture and Repairing of Airplanes (H4), Manufacture of Electronic Appliances (H9), Manufacture of Electronic Components (H10), Manufacture of Medical Equipment and Appliances (H16), Manufacture of Measuring Instrument (H17). This also means that most of the industry segments have considerable potential to improve in the efficiency of technological innovation.

4 Conclusion

This paper combines network SBM model and DEA window analysis to evaluate the technological innovation efficiency of high-tech industry in China. The conclusions of this empirical study are as follows:

1. The technological innovation efficiency shows a rising trend in the past 10 years, but the value of innovation efficiency is still low. The international financial crisis has a negative impact on the efficiency of technological innovation of china's high-tech industry in short-term. However, the conversion efficiency has been significantly improved since 2008, which prove that high-tech industry in China has a strong ability to resist risks. In addition, the CV of the overall efficiency and the conversion efficiency are both shrinking continually, but the CV of the R&D efficiency is increasing after 2007.
2. The conversion efficiency has been significantly higher than the R&D efficiency from 2002 to 2011. Furthermore, the outbreak of the international financial crisis makes China's high-tech enterprises pay more attention to enhance the conversion efficiency. The high-tech enterprises in China have pragmatism tendency, and they pay insufficient attention to the efficiency of technological R&D which reflect the industry's core competitiveness.

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