



MEASURING REGIONAL INNOVATION EFFICIENCY IN CHINA USING A DYNAMIC NETWORK DEA MODEL

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ABSTRACT

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With the explosive growth in R&D investments and patent applications in recent decades, has China truly achieved improved innovation quality? To answer this question, it is necessary to correctly estimate China's innovation efficiency. However, when measuring innovation efficiency, the dynamic and network features of the innovation process are seldom considered simultaneously. Therefore, this paper employs the method of dynamic network data envelopment analysis to estimate the overall, period, and sub-stage innovation efficiency of China's 30 provinces between 2012 and 2016. We conclude that: (1) There is a regional imbalance in the overall scores, for example, developed provinces are more efficient than less developed areas. (2) The period and sub-stage values are not high in each period and represent a gap among the various provinces. (3) For most provinces, scores in the R&D stage are higher than those in the commercialization phase, indicating an uneven distribution of the innovation structure. Accordingly, policymakers should focus on innovation efficiency indicators, encourage innovation according to local conditions, and facilitate the long-run enhancement of both R&D and commercialization.

Contribution/Originality: This paper contributes to the existing literature by employing the emerging method of dynamic network data envelopment analysis to estimate the overall, period, and divisional innovation efficiency of China in a regional context. This method not only addresses the interdependence among multiple periods in a dynamic framework but also classifies the innovation process into R&D and commercialization.

1. INTRODUCTION

Innovation is the driving force of economic and social prosperity. Especially in China, which is in a critical period of economic transformation, it is necessary to optimize the industrial structure through technological innovation and further upgrade the economic growth model from extensive to intensive. As the largest developing country, China is well on its way to putting technological innovation into practice. With the implementation of a series of domestic innovation strategies, China has grand ambitions for technological innovation and has made remarkable progress in recent decades. A series of policies, such as the “14th Five Year Plans” (FYPs) and the “Made in China 2025” (MIC25), have prompted vigorous developments in technology innovation. Those tech policies have started to pay off. For instance, according to the National Bureau of Statistics of China, the proportion of research and design (R&D) investments in the gross domestic product (GDP) in China has increased from 0.90% in 2000 to 2.19% in 2018; in addition, according to statistics from the World Intellectual Property Organization (WIPO), in

2018, the number of patent applications in China exceeded 1.54 million, and China is currently ranked first in the world, accounting for 46.40% of total global patent applications.

Despite this, the question remains whether such explosive growth in R&D investments and patent output represents an improvement in China's independent innovation capabilities. The answer is probably no. Innovation is a long-term process that includes both R&D and commercialization, with R&D at the front end of the process and commercialization at the back end (Min, Kim, & Sawng, 2020). In the R&D stage, high levels of investment do not necessarily translate as expected into knowledge; similarly, in the commercialization phase, the technology output does not inevitably transform into market value as anticipated. In this case, it is necessary to consider the indicator of innovation efficiency. Innovation efficiency refers to the input-output ratio of innovation activities, the values of which are relative and comparable among various innovators (Cruz-Cázares, Bayona-Sáez, & García-Marco, 2013; Fritsch, 2002; Guan & Chen, 2012; Min et al., 2020). It can only be achieved when more output is produced with less input. In these terms, China is not yet a real intellectual property power since it lacks high-quality patents and fails to apply technology outputs to new products or launch them profitably in the market. In other words, China's innovation efficiency is low and cannot effectively support its industrial transformation. Therefore, the accurate measurement of efficiency is the first step toward the improvement of technology innovation performance, particularly in a multi-regional economy like China.

This paper uses dynamic network data envelopment analysis (DEA) to estimate the overall, period, and sub-stage innovation efficiency of China's 30 provinces between 2012 and 2016. This paper contributes to the literature in the following ways: (1) To evaluate China's provincial innovation efficiency, the paper applies the dynamic network DEA approach, which considers both dynamic and network features. On the one hand, previous studies have mainly focused on the traditional single-period model from a static perspective, while our method addresses the interdependence among multiple periods using a dynamic framework and calculates both the overall and intertemporal efficiency scores. On the other hand, the current literature often treats innovation as a "black box," whereas we classify the innovation process into R&D and commercialization and further assess the efficiency scores of each sub-stage. (2) This paper evaluates China's innovation efficiency in a regional context. For a developing and transitional economy like China, the main innovators are not only enterprises but also research institutions and universities within an area (Li, 2009); in addition, innovation activities are related to the regional socio-economic environment and the network relationship among various innovation actors (Min et al., 2020). Therefore, when measuring innovation efficiency, the above-mentioned regional characteristics should be incorporated. (3) This paper comes to different conclusions than the previous literature. On the one hand, we find the dual characteristics of a regional imbalance and an uneven distribution of the innovation structure. Specifically, developed provinces have a higher innovation efficiency than undeveloped provinces; moreover, for most provinces, the R&D efficiency is higher than the commercialization efficiency. On the other hand, the intertemporal and divisional efficiency scores are not high in each period, and there is a disparity among the various provinces; despite this, an obvious yearly improvement in scores can still be observed.

2. LITERATURE REVIEW

The existing literature on innovation efficiency mainly deals with two topics, one focusing on the selection of measurement methods and the other on discussions of various aspects of innovation actors.

From the former perspective, when measuring efficiency, data envelopment analysis (DEA) is an essential approach (Guan & Chen, 2012). This method was first proposed by Charnes, Cooper, and Rhodes (1978) (hereinafter, CCR) and Banker, Charnes, and Cooper (1984) (hereinafter, BCC) and plays an important role in the field of operations research. Nevertheless, traditional DEA methods, such as those proposed by CCR and BCC, as well as the slacks-based measure (SBM) approach, consider the operation a "black box," a characterization that cannot appropriately capture the innovation process (Banker et al., 1984; Charnes et al., 1978; Pastor, Ruiz, &

Sirvent, 1999; Tone, 2001). Therefore, scholars have developed many other methods to calculate innovation efficiency, including network DEA (Kang, Feng, Chou, Wey, & Khan, 2022; Min et al., 2020; Wang, Pan, Pei, Yi, & Yang, 2020; Zhou & Xu, 2022), dynamic DEA (Chen, Kou, & Fu, 2018; Jiang, Ji, Shi, Ye, & Jin, 2021), super DEA (Chen, Liu, Gong, & Xie, 2021; Zhu et al., 2021), inverse DEA with frontier changes (Chen et al., 2021; Kutty, Kucukvar, Abdella, Meb, & Nco, 2022), parallel DEA (Xiong, Yang, Zhou, & Wang, 2022), Zero-Sum Gains DEA (Bouzidis & Karagiannis, 2022), DEA combined with the Malmquist-Luenberger Index (Zhang & Vigne, 2021), DEA with common weights (Arman, Jamshidi, & Hadi-Vencheh, 2021; Wang, Wu, & Chen, 2019), generalized DEA (Li, He, Shan, & Cai, 2019), and others. It is worth noting that, of all these methods, dynamic network DEA is the only one to consider the dynamic and network features of the innovation process simultaneously (Tone & Tsutsui, 2014). It has been employed in various research fields (Chang, Tone, & Wu, 2021; Del Barrio-Tellado, Gómez-Vega, Gómez-Zapata, & Herrero-Prieto, 2021; Losa, Arjomandi, Dakpo, & Bloomfield, 2020; Lu, Chiu, Yang, & Lin, 2021; See, Hamzah, & Yu, 2021; Wanke, Azad, Emrouznejad, & Antunes, 2019; Wanke, Tsionas, Chen, & Antunes, 2020; Xie, Zhou, Zong, & Lu, 2020), while only a few recent studies have applied it to estimate innovation efficiency; for instance, Liu and Lyu (2020) used it to calculate the innovation efficiency of China's pharmaceutical industries, and Bostian, Daraio, Grosskopf, Ruocco, and Weber (2020) employed it to conduct efficiency analysis at a cross-country level.

From the latter perspective, the previous literature has mainly measured innovation efficiency on the national, industrial, and firm levels. On the one hand, some have evaluated innovation efficiency within a national innovation system (NIS) framework (Guan & Chen, 2012; Li, 2009; Wilson & Vellinga, 2022). On the other hand, other studies have calculated innovation efficiency at the industrial level and made comparisons among various industries (Wang et al., 2020; Yu, Zhang, Zhang, Wang, & Cui, 2019; Zhang, Luo, & Chiu, 2019; Zuo, Guo, Li, & Cheng, 2022). Furthermore, on the firm level, scholars have not only evaluated innovation efficiency but also explored the influencing factors, such as the condition of technology or the internal management system of the business itself (Qiao, Zhao, Guo, & Tao, 2022; Xie et al., 2020; Yang, Zhang, & Li, 2022). Nevertheless, those studies have failed to deal with the discrepancies in a sub-national, regional context, which is exactly the focus of this paper. The issue of innovation efficiency in a sub-national, regional context has, nevertheless, recently received attention. For example, Chen et al. (2018) used the dynamic DEA method to evaluate China's provincial innovation efficiency and emphasized the characteristics of intertemporal dependence and the time lag in regional R&D production. Yang et al. (2022) employed the two-stage DEA method to estimate China's provincial innovation efficiency and identified both the R&D efficiency and the launch efficiency in various innovation processes. Min et al. (2020) used the two-stage network DEA method to calculate the regional innovation efficiency of both technology development and commercialization in South Korea. Generally, however, the evidence on this topic is still inconclusive and requires further exploration.

3. METHODS AND DATA

First, this paper assesses the use of the dynamic network DEA method to calculate the overall, period, and sub-stage innovation efficiency of China's 30 provinces between 2012 and 2016. We chose this method for two reasons: (1) the innovation process can be split into R&D and commercialization (Guan & Chen, 2012), yet traditional models do not cover such a network structure; (2) the innovation process is dynamic across continuous years (Chen et al., 2018), yet the previous literature has often built a static framework and estimated efficiency in a single period. Additionally, it is worth noting that the overall efficiency in our method is different from the average efficiency in traditional static models. The former regards the innovation process during the entire consecutive period as a complete dynamic procedure, while the latter simply calculates the arithmetic or geometric average of the efficiency in each sub-period. Moreover, the period and divisional efficiency refer to the interdependence in various sub-periods and the internal structure of the innovation process, respectively.

Second, we provide the below framework to analyze the above-mentioned mechanisms. Assume a production with n decision-making units (DMUs). Each $DMU_j (j = 1, \dots, n)$ includes $k (k = 1, \dots, K)$ sub-processes over $t (t = 1, \dots, T)$ periods. Each stage k involves the input M and the output N , and we represent the quantities of those two variables with M_k and N_k , respectively. $(k, h)_l$ is the link variable, which describes the inputs from stage k to stage h , and l_{kh} represents the set. k_l stands for the carry-over variable from period t to period $t+1$, and l_k indicates its set. Consequently, the input i and the output product r are defined in Equations 1 and 2, respectively; we further identify the link variable and the carry-over variable in Equation 3 and Equation 4, respectively. Furthermore, we define the weight of division k as w_k and the weight of period t as w_t . Beyond that, we apply the CRS (constant returns to scale) assumption. We set all weights even. We consider all the carry-over and link variables' desirable output. As a result, Equation 5 denotes the input-oriented dynamic network DEA model.

$$M_{ijk}^t \in R^+ (i = 1, \dots, M_k; j = 1, \dots, n; k = 1, \dots, K; t = 1, \dots, T) \tag{1}$$

$$N_{rjk}^t \in R^+ (i = 1, \dots, M_k; j = 1, \dots, n; k = 1, \dots, K; t = 1, \dots, T) \tag{2}$$

$$Z_{j(kh)_l}^t \in R^+ (j = 1, \dots, n; l = 1, \dots, L_{kh}; k = 1, \dots, K; t = 1, \dots, T) \tag{3}$$

$$Z_{jk_l}^{(t,t+1)} \in R^+ (j = 1, \dots, n; l = 1, \dots, L_{kh}; k = 1, \dots, K; t = 1, \dots, T-1) \tag{4}$$

$$\begin{aligned} & \max \theta_0^* \\ & \left\{ \begin{array}{l} M_k^t \geq \sum_{j=1}^n M_{jk}^t \lambda_{jk}^t (k = 1, \dots, K; t = 1, \dots, T) \\ N_k^t \leq \sum_{j=1}^n N_{jk}^t \lambda_{jk}^t (k = 1, \dots, K; t = 1, \dots, T) \\ Z_{(kh)_l}^t \leq \sum_{j=1}^n Z_{j(kh)_l}^t \lambda_{jk}^t ((k, h)_l = (1, \dots, K); t = 1, \dots, T) \\ Z_{(kh)_l}^t \geq \sum_{j=1}^n Z_{j(kh)_l}^t \lambda_{jh}^t ((k, h)_l = (1, \dots, K); t = 1, \dots, T) \\ Z_k^{(t,t+1)} \leq \sum_{j=1}^n Z_{jk}^{(t,t+1)} \lambda_{jk}^t (k = 1, \dots, K; t = 1, \dots, T) \\ Z_k^{(t,t+1)} \geq \sum_{j=1}^n Z_{jk}^{(t,t+1)} \lambda_{jk}^{t+1} (k = 1, \dots, K; t = 1, \dots, T) \\ \lambda_{jk}^t \geq 0 (k = 1, \dots, K; j = 1, \dots, n; t = 1, \dots, T) \\ \sum_{t=1}^T W^t = 1, W^t \geq 0 (t = 1, \dots, T) \\ \sum_{k=1}^K w_k = 1, w_k \geq 0 (k = 1, \dots, K) \end{array} \right. \tag{5} \end{aligned}$$

Third, a two-stage dynamic network structure is considered by dividing the innovation process into R&D and commercialization (see Figure 1). In the R&D stage, innovation input enters the system and transforms into innovation output; regarding innovation output, some outputs flow into the next period and are absorbed as carry-

over variables, some leave the system directly as output, while others flow into the next stage of commercialization as link variables. In the commercialization phase, the system incorporates innovation input from the outside and the link variables from the previous sub-process, separately; regarding innovation output, some outputs leave the system as final market values, while others enter the next period and are absorbed as carry-over variables.

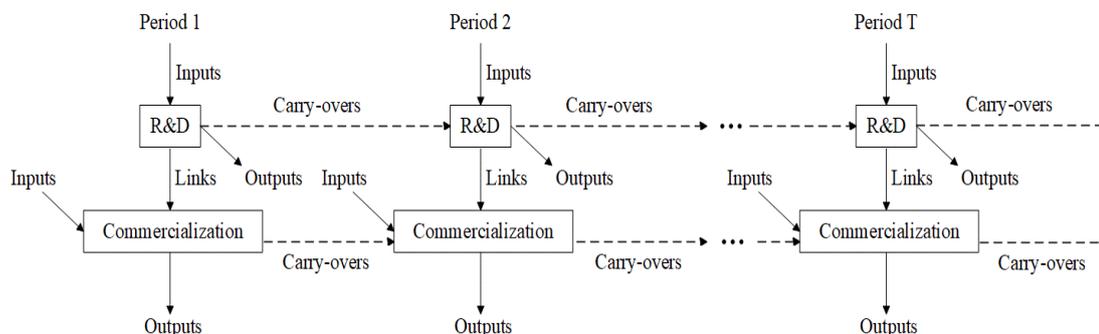


Figure 1. A dynamic model with a two-stage structure.

Table 1. Descriptive statistics of input and output variables.

Content	Variable	Unit
R&D	Full-time Equivalent of R&D Personnel (input)	Man-Year
	R&D Expenditure (input)	10,000 ¥
	Patent Applications Accepted (carry-over)	Piece
	Patent Applications Granted (link)	Piece
	Science Citation Index (SCI) Papers (output)	Piece
Commercialization	Expenditure on New Product Development (input)	10,000 ¥
	Energy Consumption (input)	104 Tce
	Patents in Force (carry-over)	Piece
	Value of Contract Deals in Domestic Technical Markets (output)	10,000 ¥
	Sales Revenue of New Products (output)	10,000 ¥

Finally, the definitions and measures of the selected variables are shown in Table 1. Data were collected from a series of statistical yearbooks released by China’s National Bureau of Statistics. Furthermore, we set a two-year lag between input, intermediates, and output, since innovation is a long-term process that demands a certain amount of time between R&D and commercialization.

4. RESULTS AND DISCUSSION

4.1. The Overall Regional Innovation Efficiency Scores in China

To compare regional innovation performance among 30 provinces in China, the overall efficiency scores were calculated and are presented in Table 2.

First, the results indicate that the average efficiency scores from 2012 to 2016 were relatively higher than the overall efficiency scores during the same period. In other words, the overall efficiency scores calculated using our method differed from the average efficiency scores measured by the traditional static single-period model, as shown in the second and third columns of Table 2. Moreover, we calculated the coefficient of variation (CV) among the provinces to measure the dispersion of the results. CV is the ratio of the standard deviation to the mean. The higher the CV, the greater the dispersion. The CV of the average efficiency values was 23.40%, which was lower than that of the overall efficiency values (33.40%), suggesting that the traditional static single-period approach underestimated the imbalance in regional innovation efficiency.

Second, a degree of spatial disparity was found in provinces’ innovation efficiency. On the one hand, the values of certain provinces (14 out of 30) were below average (0.67); in other words, the inefficient regions would have to improve their scores by at least 33.30% to catch up with the efficient provinces. On the other hand, developed

provinces, such as the capital city of Beijing and the Yangtze River Delta areas of Jiangsu and Zhejiang, have higher overall scores equaling 1. The difference between low-ranked provinces, such as the undeveloped regions of Inner Mongolia and Qinghai, and the top-ranked regions can be up to 76.70%. The possible reason may be that China's provinces have high levels of inequality in terms of economic development, industrial development, and innovation environment; this obvious regional imbalance can cause low overall innovation efficiency. As a result, compared with undeveloped provinces, developed regions have advanced innovation infrastructures and are more appealing to highly skilled innovation talents, which in turn facilitate the improvement of local innovation efficiency.

Table 2. Regional innovation efficiency in China (overall scores and intertemporal scores).

DMU	Overall Scores	Average Scores	2012	2013	2014	2015	2016
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tianjin	0.86	0.88	0.87	0.92	0.92	0.88	0.84
Hebei	0.41	0.58	0.47	0.62	0.58	0.62	0.63
Shanxi	0.34	0.56	0.43	0.60	0.56	0.60	0.59
Inner Mongolia	0.23	0.43	0.30	0.50	0.43	0.44	0.46
Liaoning	0.54	0.69	0.66	0.73	0.74	0.69	0.63
Jilin	0.94	0.97	1.00	0.86	1.00	1.00	1.00
Heilongjiang	0.70	0.78	0.56	0.78	0.82	0.89	0.83
Shanghai	0.97	0.97	1.00	1.00	1.00	1.00	0.85
Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Anhui	0.85	0.87	0.90	0.77	0.88	0.90	0.89
Fujian	0.55	0.68	0.66	0.71	0.67	0.67	0.71
Jiangxi	0.56	0.57	0.47	0.57	0.52	0.60	0.71
Shandong	0.59	0.69	0.68	0.74	0.69	0.69	0.67
Henan	0.51	0.67	0.52	0.70	0.69	0.73	0.72
Hubei	0.67	0.75	0.72	0.79	0.77	0.74	0.75
Hunan	0.79	0.78	0.80	0.75	0.75	0.80	0.82
Guangdong	0.74	0.78	0.81	0.83	0.77	0.75	0.77
Guangxi	0.59	0.57	0.51	0.52	0.46	0.58	0.78
Hainan	0.52	0.69	0.64	0.78	0.66	0.68	0.69
Chongqing	0.97	0.98	0.90	1.00	1.00	1.00	1.00
Sichuan	0.83	0.88	0.76	0.95	0.95	0.90	0.86
Guizhou	0.70	0.79	0.54	0.71	0.69	1.00	1.00
Yunnan	0.54	0.72	0.68	0.75	0.73	0.72	0.71
Shaanxi	0.70	0.75	0.72	0.74	0.77	0.79	0.74
Gansu	0.75	0.84	0.81	0.87	0.85	0.84	0.83
Qinghai	0.31	0.42	0.37	0.49	0.42	0.40	0.41
Ningxia	0.39	0.42	0.29	0.57	0.32	0.42	0.50
Xinjiang	0.47	0.67	0.53	0.68	0.69	0.68	0.75
Mean	0.67	0.75	0.69	0.76	0.75	0.77	0.77

The overall regional innovation efficiency scores in China are visualized in the geographical map in [Figure 2](#). A ladder distribution of innovation efficiency can be observed, stretching from the eastern coast to the western regions and from high to low. Specifically, developed provinces in the eastern (and some central) regions had much higher innovation efficiency scores than undeveloped provinces. For example, in the east, the capital city of Beijing and the Yangtze River Delta areas performed the best; in the midwest, Jilin, Anhui, Chongqing, and Sichuan were more efficient than the others.

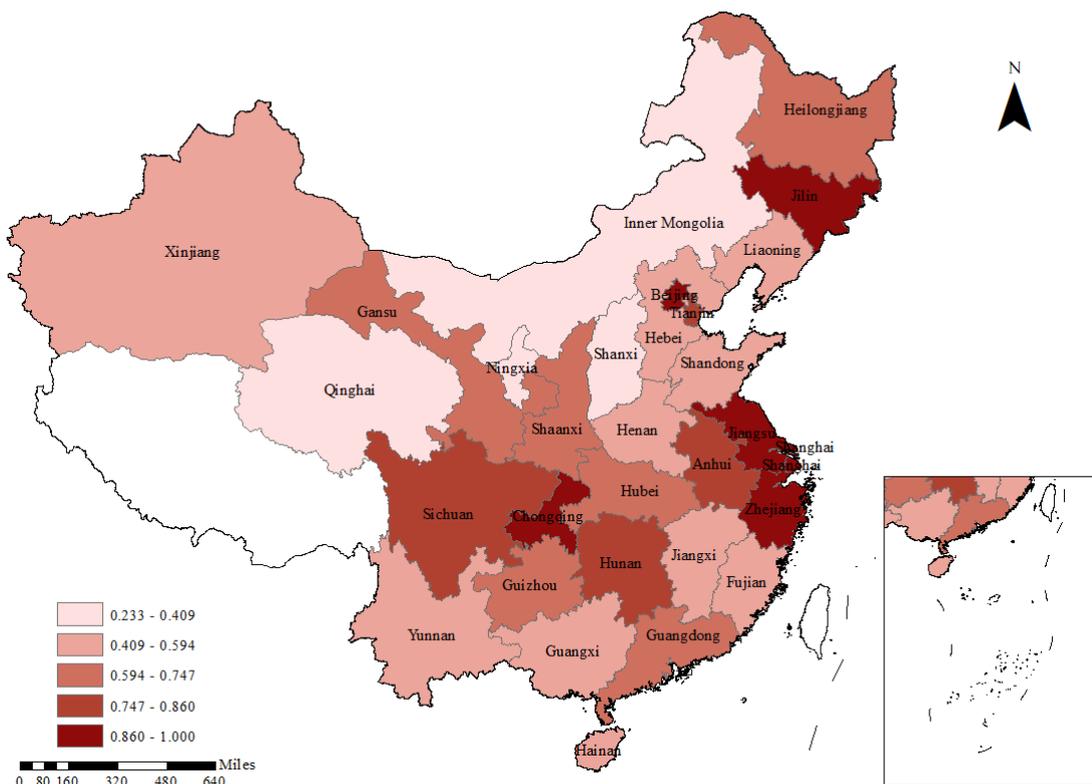


Figure 2. Spatial distribution of regional innovation efficiency in China.

4.2. The Period Scores of Regional Innovation Efficiency in China

The period scores of regional innovation efficiency in China were calculated and are also presented in Table 2.

As for the period efficiency, the difference between the average values for each year was quite low, with a range from 0.69 to 0.77. The possible reason is that innovation is a long-term process; in other words, at a given point in time, the whole innovation process is not yet completed, and the efficiency values are, therefore, still low. Yet, although the annual efficiency varied, an improvement in China’s yearly regional innovation efficiency could still be observed.

In Figure 3, we visualized the intertemporal efficiency among the 30 provinces from 2012 to 2016. The vertical axis represents the efficiency values, while the horizontal axis is the rank order of provinces from highest to lowest, according to the efficiency values. For 2012, the following characteristics can be observed: (1) The efficiency values of the top five provinces were 1, while the lowest province had an efficiency score of 0.29. In other words, the differences among the provinces were up to 71%. (2) The median value (0.68) was lower than the mean value (0.69), indicating that the period efficiency was relatively low, with more than half of the provinces having below-average scores. For 2016, the following features are presented: (1) The difference in innovation efficiency between the highest and the lowest provinces was 0.59, that is, the gap among the various provinces was up to 59%. (2) The median value (0.76) was lower than the mean value (0.77), indicating that the period efficiency was relatively low, with more than half of the provinces scoring below average.

Generally, when comparing the curves for 2012 and 2016, it can be observed that: (1) The provincial innovation efficiency scores in 2016 were generally higher than those in 2012; also, the median innovation efficiency in 2016 (0.76) was higher than that in 2012 (0.68). Therefore, the innovation efficiency in each province improved year by year. (2) The range of the 2012 data was 71%, which was much higher than that of the 2016 data (59%). Consequently, the gap in innovation efficiency among provinces was gradually narrowing. (3) Although the median value of the 2016 data showed significant improvement, it was still below the average, indicating that more than half of the provinces still had below-average efficiency values.

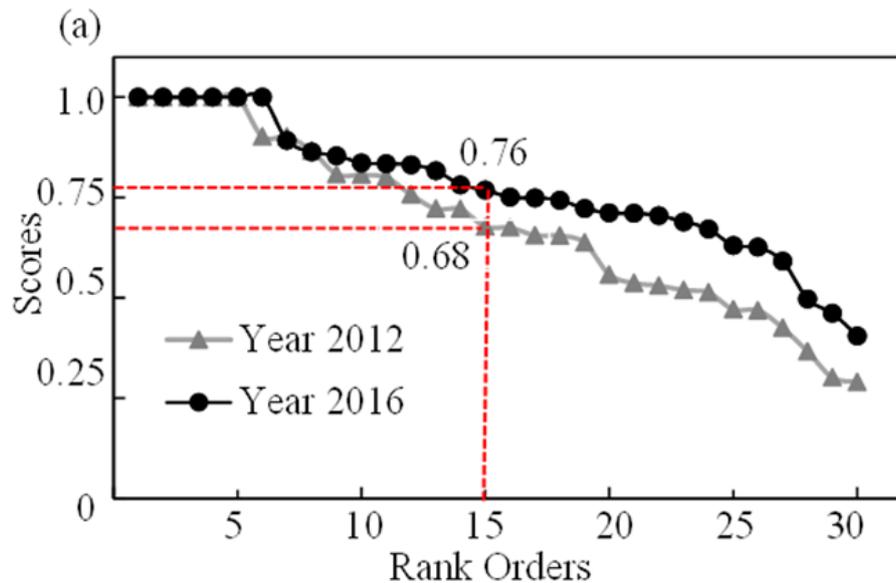


Figure 3. The rank orders of the period scores of regional innovation efficiency in China.

4.3. The Divisional Scores of Regional Innovation Efficiency in China

The divisional scores of regional innovation efficiency in China were calculated and are presented in Table 3.

First, we considered R&D efficiency. The results indicate that: (1) The average R&D efficiency score was 0.70 in 2012 and increased year on year to 0.78 in 2016, which shows an improvement trend over the entire period. (2) In 2012, 16 provinces had efficiency values above the mean (0.70), while in 2016, the number was 14. (3) The mean R&D efficiency value in the eastern regions for the entire period was 0.81, which was higher than those of the western (0.77) and interior (0.70) areas; in other words, the more developed the economy, the higher the R&D efficiency.

Second, we further explored commercialization efficiency. The results indicate that: (1) The average value in 2012 was 0.68 and rose to 0.77 in 2016, which shows an improvement over time. (2) In 2012, 12 provinces had efficiency values above the mean (0.68), while the number became 15 in 2016. (3) We found that the mean commercialization efficiency value in the eastern regions for the entire period was 0.83, which was higher than those of the western (0.70) and interior (0.67) provinces, which further supported the phenomenon that developed provinces have higher levels of commercialization efficiency.

Third, comparing the R&D and commercialization efficiency scores led us to conclude that: (1) The mean R&D efficiency value was quite low, ranging from 0.70 to 0.79 in the years under study; moreover, the average commercialization efficiency scores were not high, ranging from 0.68 to 0.77. Therefore, provinces in China display inefficiency in both R&D and commercialization. (2) The annual mean values of R&D efficiency were mostly higher than those of commercialization efficiency. Therefore, R&D was generally better developed than commercialization across China's 30 provinces.

The comparison between the R&D and commercialization efficiency in China is illustrated in Figure 4, where R&D efficiency is represented by the horizontal axis and commercialization efficiency by the vertical axis. Figure 4 (a) and Figure 4 (b) present the situation in 2012 and 2016, respectively. The red dashed line indicates the average value. It can be observed that: (1) Both in Figure 4 (a) and Figure 4 (b), the provinces are mainly distributed in the first and third quadrants, indicating a significant imbalance in R&D and commercialization efficiency among the various provinces. This observation is consistent with the overall scores. In addition, a correlation between R&D and commercialization efficiency can also be seen.

Table 3. Regional innovation efficiency in China (divisional scores).

DMU	R&D Stage					Commercialization Stage				
	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tianjin	0.73	0.83	0.84	0.76	0.67	1.00	1.00	1.00	1.00	1.00
Hebei	0.39	0.62	0.48	0.53	0.56	0.55	0.61	0.69	0.71	0.69
Shanxi	0.36	0.61	0.55	0.64	0.64	0.49	0.59	0.57	0.56	0.55
Inner Mongolia	0.23	0.48	0.39	0.36	0.35	0.38	0.51	0.47	0.51	0.57
Liaoning	0.71	0.79	0.83	0.82	0.75	0.60	0.67	0.65	0.56	0.51
Jilin	1.00	1.00	1.00	1.00	1.00	1.00	0.71	1.00	1.00	1.00
Heilongjiang	0.66	0.76	0.65	1.00	0.94	0.45	0.80	1.00	0.78	0.72
Shanghai	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	0.80
Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Anhui	1.00	1.00	1.00	1.00	0.90	0.80	0.53	0.76	0.79	0.89
Fujian	0.64	0.73	0.64	0.65	0.66	0.67	0.69	0.69	0.69	0.75
Jiangxi	0.43	0.58	0.47	0.56	0.58	0.51	0.55	0.57	0.64	0.84
Shandong	0.62	0.73	0.67	0.66	0.64	0.73	0.74	0.72	0.72	0.70
Henan	0.45	0.65	0.60	0.65	0.64	0.59	0.74	0.78	0.81	0.80
Hubei	0.77	0.84	0.79	0.81	0.79	0.67	0.73	0.74	0.67	0.71
Hunan	0.71	0.80	0.73	0.74	0.71	0.89	0.69	0.76	0.87	0.92
Guangdong	0.73	0.81	0.73	0.75	0.71	0.88	0.84	0.79	0.76	0.82
Guangxi	0.50	0.55	0.39	0.56	0.73	0.53	0.49	0.54	0.61	0.83
Hainan	0.70	0.84	0.69	0.73	0.75	0.58	0.72	0.64	0.62	0.63
Chongqing	1.00	1.00	1.00	1.00	1.00	0.80	1.00	1.00	1.00	1.00
Sichuan	0.79	0.90	0.90	0.87	0.88	0.73	1.00	1.00	0.92	0.85
Guizhou	0.57	0.73	0.66	1.00	1.00	0.51	0.69	0.72	1.00	1.00
Yunnan	0.80	0.83	0.79	0.79	0.77	0.55	0.66	0.66	0.66	0.65
Shaanxi	0.80	0.88	0.89	0.97	0.90	0.65	0.61	0.64	0.61	0.59
Gansu	1.00	1.00	1.00	1.00	1.00	0.61	0.74	0.71	0.69	0.66
Qinghai	0.32	0.52	0.47	0.44	0.43	0.41	0.46	0.38	0.35	0.38
Ningxia	0.38	0.64	0.25	0.35	0.54	0.20	0.50	0.40	0.49	0.45
Xinjiang	0.55	0.72	0.72	0.74	0.81	0.51	0.64	0.66	0.62	0.69
Mean	0.70	0.79	0.74	0.78	0.78	0.68	0.73	0.75	0.75	0.77

(2) In Figure 4 (a), 11 provinces are in the first quadrant; these are mainly developed regions, such as Beijing (BJ), Shanghai (SH), Zhejiang (ZJ), etc. The divisional efficiency scores in those regions are all above average. In contrast, 12 provinces are in the third quadrant; these are mainly undeveloped areas, such as Inner Mongolia (NM), Ningxia (NX), Qinghai (QH), etc. The divisional efficiency scores in those areas are all below the mean. The remaining provinces are in the second and fourth quadrants. Generally, developed provinces show higher divisional efficiency than undeveloped provinces, which is consistent with the above-mentioned analysis. Moreover, only Shandong (SD) is in the second quadrant, which indicates that most regions score higher in R&D efficiency than in commercialization. (3) In Figure 4 (b), the provinces are more evenly distributed across the four quadrants than in Figure 4 (a). Specifically, 9 provinces are in each of the first and third quadrants, while 6 provinces are in each of the second and fourth quadrants. This suggests an imbalance in R&D and commercialization efficiency, as previously mentioned. Furthermore, the divisional efficiency in each province is improving year after year. Two notable cases are Jiangxi (JX) and Xinjiang (XJ). In 2012, these two undeveloped regions were in the third quadrant with low divisional efficiency; however, by 2016, they had become more efficient, with Jiangxi (JX) in the second quadrant and Xinjiang (XJ) in the fourth quadrant.

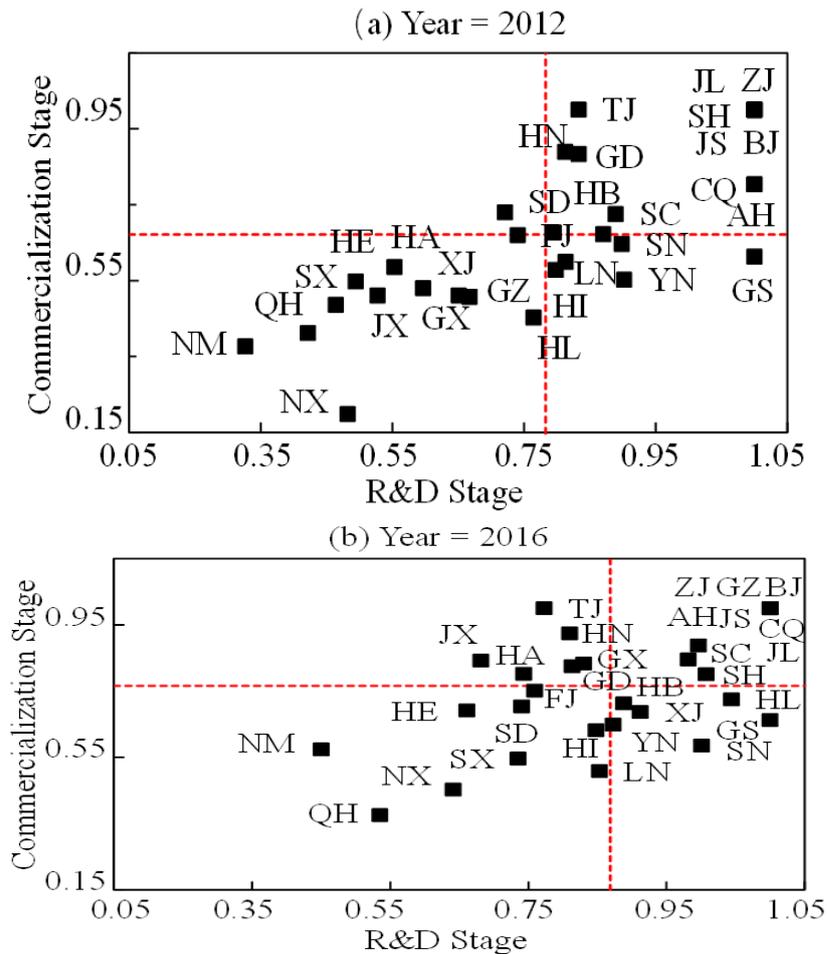


Figure 4. The comparison between R&D and commercialization efficiency in China.

5. CONCLUSIONS AND POLICY IMPLICATIONS

The controversy about high innovation investment and patent output but low innovation efficiency in developing countries such as China has garnered considerable academic interest. Under such circumstances, it is important to appropriately estimate innovation efficiency, as it plays an essential role in achieving high-quality innovation performance. Therefore, this paper employed the emerging method of dynamic network DEA to calculate the overall, period, and divisional innovation efficiency of China's 30 provinces. The results indicate that: (1) There is a regional imbalance in the overall innovation efficiency; for example, developed provinces have higher innovation efficiency than undeveloped provinces. (2) The intertemporal and divisional efficiency scores in each period are not high; despite this, an obvious yearly improvement can still be observed. (3) For most provinces, scores in the R&D stage are higher than those in the commercialization phase, indicating an uneven distribution of the innovation structure.

Based on the analysis conducted above, this paper proposes the following policy implications: (1) Policymakers should not only take efficiency indicators into account when formulating innovation policies but also employ the dynamic network DEA method to accurately assess innovation efficiency scores since it outperforms traditional static methods by covering both dynamic and network characteristics of the innovation process. (2) Due to the regional imbalance in innovation activities, policymakers should consider regional innovation conditions when formulating policies. Policymakers should maintain innovation vitality and stimulate innovation potential by promoting local innovation input and output, such as by offering tax incentives or facilitating intellectual property protection. (3) Since innovation is a long-term dynamic process, policymakers should create a stable, transparent, and continuous policy environment to stabilize innovation investment enthusiasm. (4) Since China's innovation

structure is unevenly distributed, policymakers should provide financial subsidies to attract investment and talent in the R&D stage and reduce policy approval procedures in the commercialization phase.

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