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Research Article

Innovation Efficiency Evaluation of China's High-Tech Industry considering Subindustry with a Parallel Slack-Based Measure Approach

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Although the performance estimation of technological innovation activities in the Chinese high-tech industry has been discussed continuously in prior literature, few studies analyze the imbalance development of subindustries and regional heterogeneity. Therefore, this study develops a parallel slack-based measure data envelopment analysis approach to estimate the innovation efficiency of the high-tech industry from regional and industrial perspectives. Compared with prior research, the proposed SBM-DEA model can be used to identify the inefficiencies caused by the subindustries via considering internal subindustries as parallel subunits. The proposed model is applied in the Chinese high-tech industry between 2011 and 2014. Empirical results reveal three critical findings. First, there exists an improving potential for innovation efficiency. Second, significant disparities in innovation efficiency are observed at the industrial level and regional level. Third, the inefficiency of the high-tech industry mainly stems from the low performance of the electronic equipment and communication equipment subindustry and computer and office equipment subindustry. Some suggestions for enhancing innovation efficiency are also proposed.

1. Introduction

Generally, the high-tech industry is regarded as a set of enterprises executing intense innovation activities with advanced technology foundations [1], playing a critical role in the economic development in China. Therefore, the Chinese government launched a series of innovation-related policies to facilitate innovation in the high-tech field [2], such as the national high-tech research and development program (863 programs) and "Made in China 2025." In the past decades, China's high-tech industry developed dramatically, which was reflected by the significant expansion in scale. The business income of China's high-tech sector in 2019 (i.e., 15.88 trillion RMB) is 2.66 times as large as that in 2009 (i.e., 5.96 trillion RMB) [1, 3]. The high-tech industry is an important force for innovation. However, the 2020 Global Innovation Index reports that China ranks 14th out of 131 economies. It indirectly indicates that although China's high-tech industry developed remarkably, there exists a long way to catch up with developed countries in innovation. Therefore, improving the performance in the high-tech industry is an urgent issue in China.

The first thing of performance improvement is the performance evaluation of innovation production. In existing studies, innovation production is considered as a complex transformation process of innovation resources to innovation outcomes, and the performance of innovation production can be evaluated by a comprehensive metric called "innovation efficiency" (e.g., [2, 4, 5]). Innovation efficiency is defined as the rate of resource investments to outcomes in innovation production [4]. In short, it attaches a greater innovation efficiency if it achieves more outcomes with consistent investments or achieves consistent outcomes with fewer investments. Accordingly, innovation efficiency is an appropriate indicator to quantify innovation performance. By doing so, government agencies can allocate resources more reasonably and formulate relevant policies to facilitate innovation outcomes.

Although existing performance research in the high-tech field is booming, most of them regard the high-tech sector as an integral (e.g., [4, 6, 7]). Few studies consider the inner structure to further analyze the inefficiency source of the high-tech sector by identifying the efficiency level of subindustries. In practice, the high-tech sector includes many subindustries, such as the manufacture of medical and pharmaceutical products (MPP), electronic equipment and communication equipment (EECE), computer and office equipment (COE), and medical equipment and measuring instrument (MEMI). However, unbalanced development exists in the high-tech subindustries in China [8], which results in an uneven industrial structure. For example, EECE is the largest subindustry with the greatest profit (i.e., 46.8% of the entire industry) in 2016. In addition, the development of the industry is unbalanced across different regions in China [4]. Different regions and different subindustries may have various innovation efficiencies. Consequently, to close the aforementioned knowledge gap, this paper attempts to investigate innovation performance from the perspective of subindustries and regions.

The contributions of this study are twofold. First, this paper develops a novel theoretical approach to estimate the innovation efficiency and identify the inefficiency source caused by subindustries on the strength of the data envelopment analysis (DEA) approach. The proposed parallel slack-based measure (SBM) DEA model can decompose innovation productions of the high-tech industry into four subindustries via taking each subindustry as a parallel subunit. Second, this study conducts the empirical application in China and investigates the regional disparity of innovation inefficiency, which provides some policy implications for ameliorating the innovation performance in the high-tech sector and balancing regional development.

The remaining parts of this study are structured as follows. Relevant literature is reviewed in the following Section 2. Next, the methodology for measuring innovation efficiency is illustrated in Section 3. Then, Section 4 shows the application of the proposed approach in China's high-tech sector. Finally, Section 5 summarizes the conclusions.

2. Literature Review

There are several works on innovation efficiency evaluation in the high-tech field [9–11], in which DEA is a widely applied approach [4]. DEA was created by Charnes et al. [12], and it is aimed at quantifying the relative efficiency among decision-making units (DMUs) via constructing an optimal production frontier. Due to the complexity of an innovation system, a multifactor measurement should be selected in the evaluation of innovation efficiency. DEA considers multiple inputs and outputs, so it is widely confirmed as a suitable tool to measure innovation efficiency [5, 13].

Based on the DEA method, the existing applications of the innovation efficiency evaluation of high-tech sector can be summarized into two strands: evaluations with one-stage DEA and evaluations with two-stage DEA. One strand estimates efficiency by one-stage DEA in the high-tech industry at various levels, such as enterprise, industry, and region. For example, Lu et al. [14] use the DEA method to assess the R&D efficiency of 194 Taiwanese high-tech enterprises and explore the influence factors of the efficiency. Similarly, Chen et al. [15] apply the Malmquist index approach to assess the technological innovation efficiency of six Taiwanese science and technology parks from 1991 to 1999. Raab and Kotamraju [16] investigate the technical efficiency in the high-tech sector across America's 50 states in 2002 from the perspective of regional disparity. Li et al. [7] develop a metafrontier dynamic DEA to investigate the efficiency of the Chinese regional high-tech sector. In this research direction, Han et al. [17] evaluate the R&D efficiency in the Chinese high-tech sector and investigate the effect of investment on efficiency. The above studies provide various efficiency evaluation approaches of high-tech innovation systems from different perspectives, while they fail to consider the inefficiency derived from subindustries.

The other strand of efficiency estimations deposes the innovation production process into two-stage systems to assess each stage's efficiency. For instance, Guan and Chen [6] introduce a measurement approach to investigate the performance of the entire process and internal subprocesses for China's high-tech innovations. This work divides the innovation process into R&D process and commercialization process. Zhang et al. [13] construct a Russell multiactivity network DEA model to investigate the innovation performance of R&D process and commercialization process in the Chinese high-tech sector between 2009 and 2013 and provide some specific management implications. Similarly, Wang et al. [18] propose a DEA model to explore the operation efficiency, R&D efficiency, and marketability efficiency of 65 Taiwanese high-technology enterprises during 2006-2007. From the point of innovation value chain, Chen et al. [4] construct a comprehensive evaluation model using the DEA method to investigate the efficiency of China's 29 regional high-tech sectors between 2010 and 2011. Echoing the former studies, Chen et al. [4] also develop the model with sharing inputs and accessional intermediate inputs to reveal the performance of R&D stage and commercialization stage. These studies focus mainly on the high-tech industry in an integrated manner but do not distinguish the internal subindustries and explore their performance.

Notably, the abovementioned one-stage analyses consider the innovation process as a "black box," while neglecting the multistage characteristic of the high-tech innovation [4]. Several researchers decompose the "black box" into the two-stage process: upstream process and downstream process, which can be seen as a serial structure. Moreover, the upstream process and the downstream process are interrelated with each other. Nevertheless, this type of performance evaluation without considering the internal independent subunits may not achieve a solid measurement for the unit [19, 20]. The Chinese high-tech industry contains several subindustries, which are independent of each other. The innovative activities in subindustries are conducted in parallel. Therefore, these subindustries can be deemed as a parallel structure. Each subindustry utilizes resources to acquire outputs in the actual innovation process, which leads to performance diversity across subindustries. From this

Table 1: Notation definition.

Symbol	Description
XL	R&D personnel
XC	R&D capital
XE	R&D expenditure
YP	Patents in force
YR	Sales revenue of new products
XL^h	R&D personnel of MPP, EECE, COE, and MEMI (hereinafter referred to as four subindustries), respectively
XC^h	R&D capital of four subindustries, respectively
XE^h	R&D expenditure of four subindustries, respectively
YP^h	Patents in force of four subindustries, respectively
YR^h	Sales revenue of new products of four subindustries, respectively
h	The specific subindustry h ($h = 1, 2, 3, 4$)
j	The jth decision-making unit
θ_i	Innovation efficiency for DMU i in model (1)
s_l^-	Slack variable for R&D personnel
s_c^-	Slack variable for R&D capital
s_e^-	Slack variable for R&D expenditure
s_p^+	Slack variable for patents in force
s_r^-	Slack variable for sales revenue of new products
λ_j	The participation intensity of each evaluated DMU in constructing the production frontier
ρ_i	Innovation efficiency for DMU i in model (2)
s_l^{h-}	Slack variable for R&D personnel of four subindustries, respectively
s_c^{h-}	Slack variable for R&D capital of four subindustries, respectively
s_e^{h-}	Slack variable for R&D expenditure of four subindustries, respectively
s_p^{h+}	Slack variable for patents in force of four subindustries, respectively
s_r^{h-}	Slack variable for sales revenue of new products of four subindustries, respectively
ω_h	The weights of four subindustries, respectively
λ_j^h	The participation intensity of each evaluated DMU in constructing the production frontier corresponding to four subindustries, respectively
ρ_{i1}	Innovation efficiency of MPP for DMU i in model (2)
ρ_{i2}	Innovation efficiency of EECE for DMU i in model (2)
ρ_{i3}	Innovation efficiency of COE for DMU i in model (2)
ρ_{i4}	Innovation efficiency of MEMI for DMU i in model (2)

perspective, the existing technique for estimating the innovation performance in the high-tech sector might be not solid without taking performance differences in parallel subindustries into account, which may provide insufficient evidence for policymakers. Thus, it is quite essential to estimate the innovation performance of the subindustries under the high-tech industry. However, to date, this issue has not been explored in the literature.

To address the abovementioned issue, a parallel DEA model may be adopted as it is suitable to evaluate innovation efficiency within a parallel system [21]. The concept of the parallel DEA model was proposed by Kao [22], which was designed for the measurement of the efficiency within a system with multiple individual components. The system structure can be considered as a parallel structure when each DMU has the same production process. Following Kao [22], this study regards the high-tech sector as a parallel structure. That is to say, each subindustry is a parallel subsystem. With this decomposition, the inefficiency sources hidden in the subindustries could be detected. Therefore, the efficiency evaluation considering subindustry conditions is an emerging research topic that should be paid more attention to.

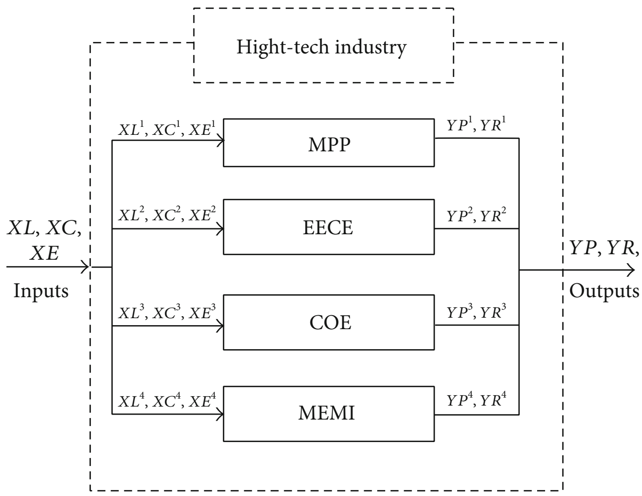

Figure 1: The high-tech industry in China with four parallel subindustries.

Overall, some studies have provided evidence on the performance assessment in the high-tech sector with one-stage or two-stage DEA methods, while most researchers ignored the internal independent subindustries. Related investigation on the innovation performance of the high-tech subindustries to explore regional disparities is still not sufficient. Therefore, the innovation performance measurement and inefficiency source identification of the high-tech sector need to be discussed further.

3. Methodology

To assess the innovation efficiency in the high-tech sector, a parallel SBM-DEA model is proposed with consideration of internal subindustry structure. In this section, the conceptual structure, related variables, and the developed parallel SBM-DEA model are illustrated. To show the model clearly, relevant notations are listed in Table 1.

3.1. Structure and Variable. The high-tech industry is composed of four subindustries (i.e., MPP, EECE, COE, and MEMI) in this study. The revenue from principal business of these four subindustries accounts for 95.53% of that of the industry in China in 2016, and they together contribute most of the innovation activities. Therefore, the high-tech industry is subdivided into four parallel subindustries. The industry structure is displayed in Figure 1.

Prior studies have proposed various input and output variables to measure innovation efficiency. Wang and Huang [23] argue that investments in innovation activity mainly include physical resources and human resources, which can be represented by R&D expenditures and R&D personnel. The two variables are widely applied in existing research (e.g., [11, 24]). To better quantify the inputs in the innovation process, Chen et al. [4] adopt R&D capital as another input variable. Accordingly, R&D personnel, R&D expenditure, and R&D capital are selected as innovation inputs in this paper. As for the innovation outputs, the granted patent is the most appropriate substitute [25, 26]. Regarding the economic benefit, the commercial value of innovation activities is regarded as an output variable [27]. Following the common practices [4, 28], the sales revenue of new products, recording the final economic output obtained from innovation activities, is another output in this research. Consequently, five input and output variables are adopted to describe the innovation process of the high-tech sector.

The innovation inputs include XL (i.e., R&D personnel), XC (i.e., R&D capital), and XE (i.e., R&D expenditure). Two outputs include YP (i.e., patents in force) and YR (i.e., sales revenue of new products). Each subindustry consumes XL, XC, and XE to produce some amount of YP and YR. XL^h, XC^h, XE^h, YP^h, and YR^h ($h = 1, 2, 3, 4$) represent the R&D personnel, R&D capital, R&D expenditure, patents in force output, and sales revenue of new products of MPP, EECE, COE, and MEMI, respectively. h expresses the specific subindustry. Note that the sum amount of input/output of four subindustries is equivalent to that of the entire high-tech industry, i.e., $XL = \sum_{h=1}^{4} XL^h$, $XC = \sum_{h=1}^{4} XC^h$, $XE = \sum_{h=1}^{4} XE^h$, $YP = \sum_{h=1}^{4} YP^h$, and $YR = \sum_{h=1}^{4} YR^h$.

3.2. Innovation Efficiency Estimation Model

3.2.1. Innovation Efficiency Estimation in an SBM-DEA Model. To estimate innovation efficiency, a province's high-tech sector is regarded as a DMU, represented as DMU_j ($j = 1, 2, \cdots, n$). In the practical innovation process, all DMUs tend to obtain desirable outputs as much as possible with inputs as little as possible. The SBM model can distinguish inefficiency sources effectively in the measurement based on the "input excess" or "output shortfall" of each variable [29, 30]. Because of this advantage, the SBM model has been broadly used in the literature (e.g., [20, 31]). Consequently, this study employs the SBM model to evaluate innovation efficiency.

Firstly, an innovation efficiency estimation model is proposed for the whole high-tech industry, which does not consider internal subindustries. The measure model is as follows:

$$
\begin{aligned}
\theta_i = \min\ & \frac{1 - 1/3\left(s_l^-/XL_i + s_c^-/XC_i + s_e^-/XE_i\right)}{1 + 1/2\left(s_p^+/YP_i + s_r^+/YR_i\right)}, \\
s.t.\ & \sum_{j=1}^{n} \lambda_j XL_j + s_l^- = XL_i, \\
& \sum_{j=1}^{n} \lambda_j XC_j + s_c^- = XC_i, \\
& \sum_{j=1}^{n} \lambda_j XE_j + s_e^- = XE_i, \\
& \sum_{j=1}^{n} \lambda_j YP_j - s_p^+ = YP_i, \\
& \sum_{j=1}^{n} \lambda_j YR_j - s_r^+ = YR_i, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j, s_l^-, s_c^-, s_e^-, s_p^+, s_r^+ \geq 0, \\
& j = 1, 2, \cdots, n,
\end{aligned}
\tag{1}
$$

of which s_l^-, s_c^-, s_e^-, s_p^+, and s_r^+ are the slack variables for

R&D personnel, R&D capital, R&D expenditure, patents in force, and sales revenue of new products in the whole high-tech sector, respectively. The slack variable expresses the evaluated DMU's "input excess" and "output shortfall" by taking the efficient DMU as the benchmark. i represents the specific DMU; λ_j represents the participation intensity of each evaluated DMU in constructing the production frontier. θ_i denotes the innovation efficiency value, being in the range of (0, 1]. If $\theta_i^* = 1$ and all slack variables are 0, the innovation efficiency of DMU i would be regarded as efficient. If not, it would be regarded as inefficient. If one DMU shows a greater efficiency value than others, it is considered that this DMU operates better than others in the innovative production process.

3.2.2. Innovation Efficiency Estimation in a Parallel SBM-DEA Model. In this study, the high-tech industry is taken as a parallel innovation system including four subindustries. Referring to Kao [22] and Kao and Hwang [32], the innovation efficiency of the high-tech industry with the consideration of parallel subindustries could be measured through the following formula:

$$
\begin{aligned}
&\rho_i = \min \frac{\sum_{h=1}^{4}\omega_h\left[1 - 1/3\left(s_l^{h-}/XL_i^h + s_c^{h-}/XC_i^h + s_e^{h-}/XE_i^h\right)\right]}{\sum_{h=1}^{4}\omega_h\left[\left(1 + 1/2\left(s_p^{h+}/YP_i^h + s_r^{h+}/YR_i^h\right)\right)\right]},\\
&\text{s.t.} \sum_{j=1}^{n}\lambda_j^1 XL_j^1 + s_l^{1-} = XL_i^1,\ \sum_{j=1}^{n}\lambda_j^1 XC_j^1 + s_c^{1-} = XC_i^1,\ \sum_{j=1}^{n}\lambda_j^1 XE_j^1 + s_e^{1-} = XE_i^1,\\
&\quad \sum_{j=1}^{n}\lambda_j^1 YP_j^1 - s_p^{1+} = YP_i^1,\ \sum_{j=1}^{n}\lambda_j^1 YR_j^1 - s_r^{1+} = YR_i^1,\\
&\sum_{j=1}^{n}\lambda_j^2 XL_j^2 + s_l^{2-} = XL_i^2,\ \sum_{j=1}^{n}\lambda_j^2 XC_j^2 + s_c^{2-} = XC_i^2,\ \sum_{j=1}^{n}\lambda_j^2 XE_j^2 + s_e^{2-} = XE_i^2,\\
&\sum_{j=1}^{n}\lambda_j^2 YP_j^2 - s_p^{2+} = YP_i^2,\ \sum_{j=1}^{n}\lambda_j^2 YR_j^2 - s_r^{2+} = YR_i^2,\\
&\sum_{j=1}^{n}\lambda_j^3 XL_j^3 + s_l^{3-} = XL_i^3,\ \sum_{j=1}^{n}\lambda_j^3 XC_j^3 + s_c^{3-} = XC_i^3,\ \sum_{j=1}^{n}\lambda_j^3 XE_j^3 + s_e^{3-} = XE_i^3,\\
&\sum_{j=1}^{n}\lambda_j^3 YP_j^3 - s_p^{3+} = YP_i^3,\ \sum_{j=1}^{n}\lambda_j^3 YR_j^3 - s_r^{3+} = YR_i^3,\\
&\sum_{j=1}^{n}\lambda_j^4 XL_j^4 + s_l^{4-} = XL_i^4,\ \sum_{j=1}^{n}\lambda_j^4 XC_j^4 + s_c^{4-} = XC_i^4,\ \sum_{j=1}^{n}\lambda_j^4 XE_j^4 + s_e^{4-} = XE_i^4,\\
&\sum_{j=1}^{n}\lambda_j^4 YP_j^4 - s_p^{4+} = YP_i^4,\ \sum_{j=1}^{n}\lambda_j^4 YR_j^4 - s_r^{4+} = YR_i^4,\\
&\sum_{j=1}^{n}\lambda_j^h = 1, h = 1, 2, 3, 4,\\
&\quad s_l^{h-}, s_c^{h-}, s_e^{h-}, s_p^{h+}, s_r^{h+} \geq 0,\\
&\qquad \lambda_j^h \geq 0,\\
&\qquad j = 1, 2, \cdots, n.
\end{aligned}
\tag{2}
$$

Similarly, ρ_i expresses the innovation efficiency in the high-tech industry for DMU i, also being in the range of (0, 1]. s_l^{i-}, s_c^{i-}, s_e^{i-}, s_p^{i+}, and s_r^{i+} are slack variables attached to R&D personnel, R&D capital, R&D expenditure, patents in force, and sales revenue of new products for four subindustries, respectively. ω_h $(h = 1, 2, 3, 4)$ denotes the exogenous weights of four subindustries, meeting the constraint: $\sum_{h=1}^{4}\omega_h = 1$; λ_j^i $(h = 1, 2, 3, 4)$ represents the participation intensity of each evaluated DMU for constituting the production frontier.

Note that the optimal solutions obtained under model (2) for measuring innovation efficiency can be used to calculate the efficiencies of four subindustries further, i.e., ρ_{i1}, ρ_{i2}, ρ_{i3}, and ρ_{i4}, respectively. Specifically, the slack variables for MPP, EECE, COE, and MEMI are optimized to get the overall innovation efficiency in model (2). By solving model (2), the efficiencies of four subindustries can be calculated by the corresponding formulas.

$$
\rho_{i1} = \min \frac{1 - 1/3\left(s_l^{1-}/XL_i^1 + s_c^{1-}/XC_i^1 + s_e^{1-}/XE_i^1\right)}{1 + 1/2\left(s_p^{1+}/YP_i^1 + s_r^{1+}/YR_i^1\right)}, \tag{3}
$$

$$
\rho_{i2} = \min \frac{1 - 1/3\left(s_l^{2-}/XL_i^2 + s_c^{2-}/XC_i^2 + s_e^{2-}/XE_i^2\right)}{1 + 1/2\left(s_p^{2+}/YP_i^2 + s_r^{2+}/YR_i^2\right)}, \tag{4}
$$

$$
\rho_{i3} = \min \frac{1 - 1/3\left(s_l^{3-}/XL_i^3 + s_c^{3-}/XC_i^3 + s_e^{3-}/XE_i^3\right)}{1 + 1/2\left(s_p^{3+}/YP_i^3 + s_r^{3+}/YR_i^3\right)}, \tag{5}
$$

$$
\rho_{i4} = \min \frac{1 - 1/3\left(s_l^{4-}/XL_i^4 + s_c^{4-}/XC_i^4 + s_e^{4-}/XE_i^4\right)}{1 + 1/2\left(s_p^{4+}/YP_i^4 + s_r^{4+}/YR_i^4\right)}. \tag{6}
$$

Based on model (2) and equations (3)–(6), the overall innovation efficiency and subindustries' efficiencies can be both obtained. In addition, we can derive a conclusion that the high-tech industry is overall efficient if and only if all subindustries are efficient.

4. Empirical Study

The above parallel SBM-DEA model is utilized to evaluate the innovation performance in China's high-tech sector. This section first illustrates the data source. Then, the results of regional innovation efficiency are presented and discussed.

4.1. Data Source. The Chinese mainland has 31 province-level regions, while due to data lacking, some regions are not included in this study. Our samples include 17 regions in China. Following Hu and Wang [33], these regions are further classified into three major areas. Beijing, Shanghai, Tianjin, Liaoning, Hebei, Zhejiang, Shandong, Guangdong, Fujian, and Jiangsu belong to the east area. The center area includes Henan, Hunan, Jiangxi, Hubei, and Anhui. Shaanxi and Sichuan are in the west area.

As mentioned above, five variables, including inputs and outputs, are used for quantifying innovation efficiency. In this study, R&D personnel adopts the sum of research employees, including designers, engineers, and relevant staff who are crucial participants in R&D activities. R&D

expenditure is the total expenses on internal R&D activities of enterprises per year. R&D capital refers to the accumulated resource stock in enterprises, providing basic support for innovation activities. Nevertheless, there are no official statistical data on the R&D capital for China's high-tech sector. Hence, following Chen et al. [4], the perpetual inventory method is also utilized to assess R&D capital. The year 2000 is regarded as the base period. The depreciation rate is set as 8%. This study also takes the data of the year 2000 divided by 10% as the base level. For the introduction to the perpetual inventory method, see Hall and Jones [34]. Patents in force refer to the total valid patents that can be used in enterprises [35]. Sales revenue of new products is the total sale returns of new products.

The annual data of inputs and outputs from 2011 to 2016 are acquired from China Statistical Yearbook on the High Technology Industry. Furthermore, in prior literature, the time lag effect between innovation activities and commercial operation is a significant consideration for the innovation performance analysis. Referring to Guan and Chen [6] and Hong et al. [36], this paper also sets a 1-year lag for the patents in force after R&D inputs and then another 1-year lag for the sales revenue. Additionally, all currency data are transformed at the 2011 price for removing the inflation impact. Table 2 displays five variables' descriptive statistics in 2011.

4.2. Innovation Efficiency Analysis. To calculate innovation efficiency by the proposed model, the weights for four subindustries need to be determined first. In the literature, the industry structure proportion (ISP) is an appropriate indicator to measure subindustries' weights [31, 37–40]. The high-tech industry structure proportion (HISP) refers to the proportion of the main business income of a subindustry to that of the entire industry in this study. The average HISP values of MPP, EECE, COE, and MEMI during the period of 2013 to 2016 are 0.1839, 0.5369, 0.1715, and 0.0763, respectively. Hence, the weights of four subindustries can be determined according to the corresponding average HISP values (i.e., $\omega_1 = 0.1839/(0.1839 + 0.5369 + 0.1715 + 0.0763) = 0.1899$, $\omega_2 = 0.5543$, $\omega_3 = 0.1771$, and $\omega_4 = 0.0788$).

4.2.1. Analysis from an Overall Perspective. The efficiency results under model (2) are listed in Table 3. It can be seen that the innovation efficiencies of the high-tech sector between 2011 and 2014 are in the range of [0.5, 0.6]. The overall innovation efficiency rises slightly while still at a lower level [41, 42]. This implies that there exists much improvement room for the innovation performance in China's high-tech sector.

Moreover, distinct differences in subindustry efficiencies are observed. Specifically, the average efficiency values of MPP, EECE, COE, and MEMI subindustries during 2011-2014 are 0.746, 0.516, 0.497, and 0.660, respectively. The average innovation efficiency value of MPP is the largest, followed by MEMI and EECE, while COE performs the worst [43, 44]. The efficiency gap between MPP and COE is 0.249. This indicates that the unbalanced development among subindustries should be concerned. The resource investment into each subindustry needs to be comprehensively considered. In addition, in 2011 and 2012, COE is observed with the lowest efficiency value among four subindustries (i.e., 0.451 and 0.480), while in 2013 and 2014, EECE has the lowest efficiency value (i.e., 0.528 and 0.483). It indicates that the inefficiencies in the high-tech sector are primarily derived from the poor performances of EECE and COE. Therefore, EECE and COE should be given priority over MPP and MEMI for their lower performances.

Furthermore, Figure 2 displays the results of the high-tech industry's innovation efficiency among 17 regions. As shown, the disparities among regions are observed distinctly. Beijing and Guangdong have higher innovation efficiencies (more than 0.8) during the observed period. Specifically, only Beijing performs efficiently during 2011-2013, while it performs inefficiently in 2014 (i.e., 0.847). The innovation efficiencies of most regions (e.g., Henan, Hunan, Tianjin, Jiangsu, Shanghai, and Shandong) are in the range of [0.4, 08], whereas Hebei has the lowest innovation efficiency value from 2011 to 2014 (i.e., 0.227, 0.279, 0.308, and 0.273, respectively). This suggests that there exists a great potential to improve innovation performance in Hebei.

4.2.2. Analysis from a Subindustry Perspective. To further analyze the subindustry disparities in innovation efficiencies, the mean innovation efficiencies in regions and areas from 2011 to 2014 are shown in Table 4.

For MPP, it can be observed that Beijing, Tianjin, and Hunan perform efficiently. The innovation efficiency values of Shanghai, Jiangsu, Zhejiang, Anhui, Shandong, and Sichuan (i.e., 0.852, 0.834, 0.870, 0.903, 0.948, and 0.796, respectively) are higher than the overall average (i.e., 0.746). Particularly, the innovation efficiency values of Liaoning and Henan (i.e., 0.401 and 0.353) are the lowest two. This indicates that the innovation activities of MPP are undeveloped in Liaoning and Henan. Hence, the local governments should take more measures to stimulate pharmaceutical enterprises to launch R&D activities and improve innovation outcomes.

In terms of EECE, only Henan and Guangdong are rated as efficient. The efficiency values of Beijing, Zhejiang, Shanghai, and Sichuan are observed higher than the overall average (i.e., 0.516). Furthermore, the differences in the efficiency of EECE across the three areas are small. The probable reason may be that there exist few differences in technical innovation among the EECE enterprises in China. Accordingly, it indicates that the regional disparities in EECE have been largely eliminated or abated.

Concerning COE, only Beijing and Jiangsu are observed efficient innovation performance. The innovation efficiency values of Tianjin, Anhui, Shandong, Guangdong, Sichuan, and Shaanxi are above the overall average (i.e., 0.497). Interestingly, the west area (i.e., 0.723) performs better than the east area (i.e., 0.538) and the center area (i.e., 0.322) on average. This indicates that innovation resources have been utilized more effectively in COE in the western regions. It also implies that the inefficiencies of some central and eastern provinces are mainly derived from the poor innovation

Table 2: Descriptive statistics of the dataset in 2011.

Industries	Statistics	R&D personnel (person)	R&D capital (10^8 CNY[1])	R&D expenditure (10^8 CNY)	Patents in force (piece)	Sales revenue of new products (10^8 CNY)
MPP	Maximum	14729.00	790.14	40.48	1916.00	617.55
	Minimum	1230.00	57.84	1.61	158.00	29.39
	Mean	5851.94	325.28	13.22	743.53	177.25
	Std. Dev.	4333.60	207.50	12.80	552.45	153.02
EECE	Maximum	155018.00	3969.29	409.05	48352.00	6878.03
	Minimum	1389.00	249.70	2.08	68.00	48.58
	Mean	18695.18	750.34	47.90	4187.76	1083.52
	Std. Dev.	35676.92	918.49	93.52	11144.37	1585.93
COE	Maximum	21669.00	628.34	52.01	9553.00	2314.44
	Minimum	37.00	4.03	0.02	1.00	0.34
	Mean	3319.06	125.93	9.43	953.18	321.60
	Std. Dev.	5496.66	180.08	14.26	2287.69	688.86
MEMI	Maximum	21625.00	1093.67	39.94	2666.00	545.84
	Minimum	16.00	22.68	0.03	38.00	9.13
	Mean	4355.53	156.24	7.80	594.35	93.88
	Std. Dev.	5303.95	240.88	9.57	734.46	135.67

[1]CNY represents China Yuan.

Table 3: Efficiency results under model (2).

Year	ρ	ρ_1	ρ_2	ρ_3	ρ_4
2011	0.546	0.683	0.513	0.451	0.662
2012	0.582	0.747	0.542	0.480	0.702
2013	0.589	0.780	0.528	0.556	0.635
2014	0.553	0.773	0.483	0.499	0.641
Mean	0.568	0.746	0.516	0.497	0.660

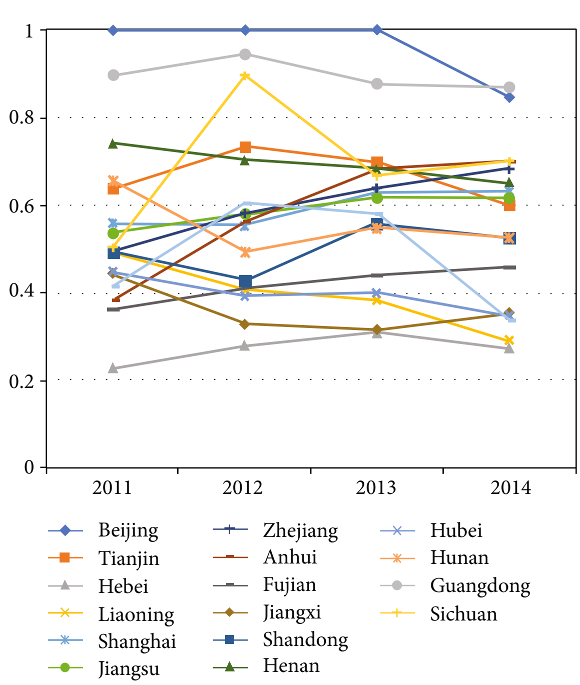

Figure 2: Innovation efficiencies in regions.

efficiencies in COE (e.g., Hebei, Hubei, Henan, and Liaoning).

Regarding MEMI, four provinces (i.e., Beijing, Hunan, Zhejiang, and Guangdong) are rated as efficient. The efficiency values of Tianjin, Jiangsu, Shanghai, and Sichuan are larger than the overall average (i.e., 0.660). China's east area (i.e., 0.723) operates better than the center area (i.e., 0.570) and the west area (i.e., 0.570). The performance gap between the central and western provinces and the eastern provinces should be narrowed, especially for Jiangxi and Shaanxi. In addition, it is worth noting that some eastern regions also should improve innovation efficiencies urgently, such as Hebei (i.e., 0.336), Fujian (i.e., 0.450), and Shandong (i.e., 0.544), whose efficiency values are lower than the overall average.

The inefficiency sources of regional innovation are also identified. For some regions, such as Hebei and Hubei, the innovation efficiency values of EECE and COE are found to be lower. This indicates the innovation inefficiencies of these regions are attributed to the low efficiency of EECE and COE. Significant disparities of innovation efficiency are found in four subindustries at the areal level. The east area remains ahead in MPP, EECE, and MEMI, while the west area has the highest innovation efficiency value in COE. Additionally, the west area also shows a better innovation level in EECE, COE, and MEMI than the center area. Notably, the phenomenon of higher innovation efficiency seems to be more likely to exist in more developed regions. It can be explained as more investments accelerate the technological innovation and management improvement of high-tech enterprises in economically developed regions, thus motivating more innovation outputs effectively. Considering the areal disparity, the balanced development of subindustries in the provinces should be concerned.

Table 4: Mean innovation efficiency results in regions under model (2).

Region	ρ	ρ_1	ρ_2	ρ_3	ρ_4
Beijing	0.962	1.000	0.931	1.000	1.000
Tianjin	0.668	1.000	0.498	0.731	0.916
Hebei	0.272	0.519	0.219	0.144	0.336
Liaoning	0.393	0.401	0.415	0.229	0.591
Shanghai	0.593	0.852	0.586	0.286	0.708
Jiangsu	0.587	0.834	0.357	1.000	0.684
Zhejiang	0.599	0.870	0.557	0.259	1.000
Anhui	0.582	0.903	0.475	0.578	0.569
Fujian	0.417	0.536	0.382	0.386	0.450
Jiangxi	0.360	0.646	0.259	0.394	0.307
Shandong	0.500	0.948	0.294	0.646	0.544
Henan	0.695	0.353	1.000	0.219	0.439
Hubei	0.397	0.684	0.355	0.161	0.534
Hunan	0.555	1.000	0.434	0.262	1.000
Guangdong	0.897	0.733	1.000	0.702	1.000
Sichuan	0.691	0.796	0.625	0.779	0.707
Shaanxi	0.484	0.602	0.393	0.668	0.433
East	0.589	0.769	0.524	0.538	0.723
Center	0.518	0.717	0.504	0.322	0.570
West	0.588	0.699	0.509	0.723	0.570

4.2.3. Analysis from Temporal and Areal Perspectives. The changing trend of areal innovation efficiency value during 2011-2014 is displayed in Figure 3. As shown, the overall innovation performance of the high-tech sector rises slightly during the observed time. The dynamic trends in the east area and the center area are close to the overall one, while the one in the west area shows great fluctuation. There are two possible reasons. For one thing, the development of most subindustries in the west area may be immature and relatively backward, which is more susceptible to internal and external factors. For another, the west area only includes two provinces, and the small sample size may lead to this fluctuation phenomenon.

The areal innovation efficiencies of four subindustries are also presented in Figure 4. Overall, the efficiency of MECE shows an increasing trend from 2011 to 2014, which is consistent with the high-tech industry. Besides, the efficiency gap between the three regions has been narrowed slightly, whereas those of MPP, COE, and MEMI show a declining trend. It can be found that the east area always takes the leading position in MPP and MEMI from 2012 to 2014. It suggests that the eastern developed regions invest more R&D resources in technological innovation in the medical industry, which have contributed to advanced technology and market advantages, resulting in higher innovation efficiency. Notably, the west area has the highest average efficiency in COE than the other two areas since 2012. It might be related to the technical input and industrial transfer of COE in the western provinces. It indicates that the western regions probably may utilize resources more efficiently and promote the prosperity and development of COE. Additionally, higher volatility is observed in the west area in four subindustries. This also indirectly accounts for the performance fluctuation at the industry level in the west area.

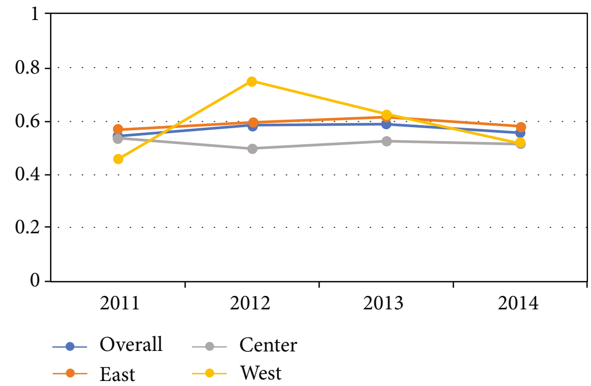

Figure 3: Innovation efficiency in areas.

4.3. Result Comparison. As mentioned above, model (1) is constructed to evaluate innovation efficiency without considering parallel subindustries, and model (2) is proposed to estimate innovation efficiency considering subindustries. To examine the effectiveness of the proposed method, this paper makes a comparative analysis between the results under two models. Table 5 presents the efficiency results.

Under model (1), only Henan and Guangdong stay efficient from 2011 to 2014. Beijing and Tianjin perform efficiently from 2011 to 2013, while both of them perform inefficiently in 2014 (i.e., 0.759 and 0.764). Additionally, Sichuan is observed as efficient in 2012, while Hebei has the lowest average innovation efficiency value from 2011 to 2014.

There exist differences in innovation efficiency results obtained from the two models. Here, the result of the year 2011 is taken as an example. As shown in Table 5, Beijing, Tianjin, Henan, and Guangdong are rated as efficient in model (1) in 2011, while only Beijing is observed as efficient in model (2). This is because the efficiency values of Beijing's four subindustries are 1.000. In contrast, Tianjin (i.e., 0.637), Henan (i.e., 0.741), and Guangdong (i.e., 0.895) are regarded as inefficient in model (2) because of the inefficiencies of subindustries (i.e., 1.000, 0.525, 0.470, and 0.931; 0.429, 1.000, 0.313, and 0.638; and 0.449, 1.000, 1.000, and 1.000, respectively). This result reveals that the innovation inefficiency of the industry is connected with the performances of the subindustries. Namely, the inefficiency may stem from one subindustry or multiple subindustries. Therefore, we can identify the inefficiency sources from subindustries in model (2). For instance, the high-tech industry of Hebei is deemed inefficient in two models (i.e., 0.275 and 0.227). It can be reasonably inferred that the inefficiency of Hebei is primarily derived from EECE and COE for their low efficiencies in model (2), which cannot be identified in model (1). The proposed evaluation model may offer more implications on innovation performance, which not only focuses on the high-tech industry's innovation efficiency but also considers which subindustries make it effective (or ineffective).

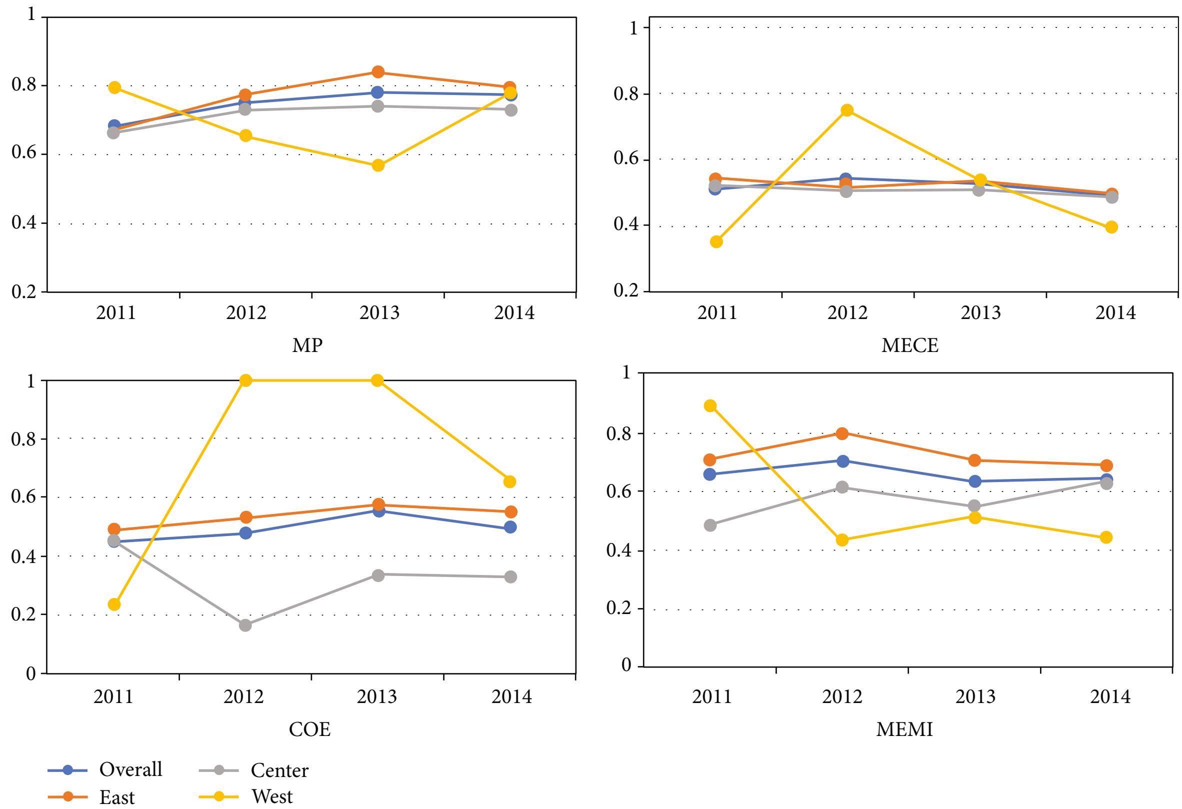

Figure 4: Average innovation efficiencies in four subindustries.

4.4. Discussion and Implications. The proposed model and empirical results offer a new horizon of the innovation performance in China's high-tech sector. Discussion and implications are also provided in this subsection.

At the industry level, the overall innovation performance rises slightly, yet still at a lower level. This finding is consistent with prior research conclusions (e.g., [6, 7]) that there exists a great improvement potential for the innovation performance in China's high-tech sector. Moreover, in comparison with prior research, the proposed evaluation model provides a tool to identify the inefficiency source of the overall high-tech industry. Besides, at the subindustry level, innovation performance is significantly unbalanced. Specifically, EECE and COE should be given priority over MPP and MEMI owing to their lower performances. Therefore, the improvement of innovation performance should consider not only the high-tech industry's conditions but also the subindustries' conditions.

The findings also provide empirical evidence for stimulating the development of the high-tech sector in China. The lower efficiency of one or multiple subindustries leads to lower regional innovation efficiency. Therefore, the inefficiencies of particular subindustries should be emphasized and improved. For example, Hebei should focus on increasing COE's efficiency (i.e., 0.144) first and then EECE's efficiency (i.e., 0.219), MEMI's efficiency (i.e., 0.336), and MPP's efficiency (i.e., 0.519). Moreover, significant regional disparities in innovation efficiencies are also identified. The finding that higher innovation efficiencies are more possibly existed in more developed regions echoes the prior studies of Chen et al. [4] and Zhang et al. [13]. This is because more resource input stimulates technological innovation in economically developed regions, thus increasing more innovation outputs.

Based on the empirical findings, some implications are provided to improve industrial innovation efficiency as follows. First, the balanced development of subindustries should be drawn more attention. The government should provide more support (e.g., tax reduction and subsidies) for the subindustries with lower efficiency (e.g., EECE and COE). The targeted supports for subindustries that innovation inefficient may help to strengthen the performance more effectively. Second, regional collaboration should be encouraged by the government in the high-tech sector. Specifically, policymakers in backward regions can learn innovation management experiences from advanced ones. The government can also build a platform to promote cross-regional collaboration, which may facilitate R&D resource sharing, enterprise communication, and cross-industry innovation. These collaborations may help underdeveloped enterprises to learn innovative managerial experiences from high performed enterprises and narrow the gaps in innovation among areas. Third, local governments should develop industry innovation policies according to the specific conditions of local subindustries. More resources and policy supports should be offered for subindustries with lower performance as their innovation development has severely hindered the overall industry performance. Inappropriate

Table 5: Innovation efficiency results based on model (1) and model (2).

Region	2011						2012						2013						2014					
	θ	ρ	ρ_1	ρ_2	ρ_3	ρ_4	θ	ρ	ρ_1	ρ_2	ρ_3	ρ_4	θ	ρ	ρ_1	ρ_2	ρ_3	ρ_4	θ	ρ	ρ_1	ρ_2	ρ_3	ρ_4
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.759	0.847	1.000	0.724	1.000	1.000
Tianjin	1.000	0.637	1.000	0.525	0.470	0.931	1.000	0.734	1.000	0.520	1.000	1.000	1.000	0.699	1.000	0.456	1.000	1.000	0.764	0.600	1.000	0.491	0.454	0.734
Hebei	0.275	0.227	0.438	0.180	0.073	0.392	0.300	0.279	0.539	0.214	0.174	0.348	0.310	0.308	0.610	0.266	0.133	0.268	0.269	0.273	0.488	0.215	0.194	0.337
Liaoning	0.488	0.493	0.558	0.542	0.271	0.483	0.436	0.407	0.425	0.379	0.209	1.000	0.384	0.383	0.305	0.461	0.238	0.347	0.296	0.290	0.315	0.276	0.198	0.535
Shanghai	0.472	0.559	0.590	0.687	0.138	0.525	0.482	0.554	0.818	0.530	0.217	0.848	0.562	0.628	1.000	0.582	0.315	0.763	0.520	0.630	1.000	0.544	0.475	0.696
Jiangsu	0.439	0.536	0.574	0.355	1.000	0.672	0.501	0.581	0.877	0.334	1.000	0.660	0.584	0.618	1.000	0.363	1.000	0.624	0.648	0.615	0.886	0.376	1.000	0.781
Zhejiang	0.503	0.493	0.649	0.413	0.353	1.000	0.514	0.582	0.829	0.605	0.059	1.000	0.748	0.637	1.000	0.589	0.235	1.000	0.695	0.683	1.000	0.623	0.390	1.000
Anhui	0.350	0.384	0.613	0.380	0.215	0.236	0.583	0.562	1.000	0.530	0.217	0.505	0.662	0.682	1.000	0.531	0.878	0.535	0.600	0.700	1.000	0.458	1.000	1.000
Fujian	0.456	0.361	0.420	0.365	0.296	0.344	0.496	0.410	0.545	0.348	0.400	0.545	0.579	0.439	0.634	0.376	0.383	0.540	0.642	0.458	0.544	0.439	0.465	0.373
Jiangxi	0.255	0.443	0.665	0.233	1.000	0.135	0.373	0.329	0.572	0.281	0.184	0.398	0.355	0.314	0.620	0.256	0.154	0.346	0.389	0.355	0.729	0.265	0.236	0.349
Shandong	0.368	0.491	1.000	0.341	0.322	0.700	0.347	0.428	1.000	0.261	0.263	0.592	0.486	0.557	1.000	0.274	1.000	0.479	0.509	0.525	0.791	0.299	1.000	0.403
Henan	1.000	0.741	0.429	1.000	0.313	0.638	1.000	0.703	0.381	1.000	0.222	0.473	1.000	0.682	0.304	1.000	0.233	0.370	1.000	0.651	0.298	1.000	0.106	0.277
Hubei	0.312	0.448	0.627	0.429	0.329	0.415	0.297	0.393	0.698	0.359	0.042	0.692	0.357	0.401	0.784	0.340	0.134	0.506	0.296	0.347	0.628	0.292	0.138	0.523
Hunan	0.565	0.656	1.000	0.564	0.419	1.000	0.579	0.493	1.000	0.352	0.166	1.000	0.683	0.548	1.000	0.409	0.298	1.000	0.678	0.525	1.000	0.410	0.165	1.000
Guangdong	1.000	0.895	0.449	1.000	1.000	1.000	1.000	0.945	0.712	1.000	1.000	1.000	1.000	0.877	0.861	1.000	0.454	1.000	1.000	0.869	0.912	1.000	0.354	1.000
Sichuan	0.442	0.502	1.000	0.385	0.115	1.000	1.000	0.895	0.609	1.000	1.000	0.608	0.606	0.667	0.576	0.603	1.000	0.586	0.506	0.700	1.000	0.510	1.000	0.633
Shaanxi	0.366	0.414	0.590	0.318	0.358	0.786	0.356	0.605	0.700	0.495	1.000	0.261	0.398	0.580	0.562	0.473	1.000	0.436	0.261	0.338	0.555	0.285	0.312	0.251
Mean	0.547	0.546	0.683	0.513	0.451	0.662	0.604	0.582	0.747	0.542	0.480	0.702	0.630	0.589	0.780	0.528	0.556	0.635	0.578	0.553	0.773	0.483	0.499	0.641

or unbalanced resource allocation may induce resource waste and achieve unsatisfactory innovation outputs. For example, Tianjin, Jiangsu, and Shandong should enhance the efficiency of EECE; Hubei should strengthen the efficiency of EECE and COE, while Hebei should make efforts to improve the efficiencies of four subindustries.

5. Conclusion

This study establishes a parallel SBM-DEA model to assess the innovation performance of the high-tech sector with the consideration of internal subindustries. Different from prior research on innovation efficiency evaluations, this study provides a novel theoretical approach to identify the inefficiency sources from internal subindustries. Moreover, the proposed approach is utilized to calculate the innovation efficiencies in China's regional high-tech industries and four subindustries between 2011 and 2014.

Overall, the findings can be summarized as follows. First, although the innovation efficiency of China's high-tech sector is still at a low level, it slightly increased with the fluctuation during the study period. That is to say, the immense potential exists for enhancing the utilization efficiency of innovation resources. Second, the inefficiency of the Chinese high-tech sector probably stems from the inefficient performances in EECE and COE. That being said, these two subindustries may be considered as key factors to improve innovation performance, so their development should obtain more concerns and supports from the government. Third, the regional differences and industrial differences are significant in the innovation efficiency of four subindustries. In terms of MPP, EECE, and MEMI, the innovation efficiency averages of eastern China perform better than those of central China and western China. In addition, COE in the west area is observed a higher efficiency average than that in the east area and center area. This finding suggests that policymakers should consider the importance of regional disparities and industrial disparities for better resource allocation to support innovation activities.

This study is also not free from limitations. First, this paper does not take the subprocess into account in innovation efficiency evaluation, such as the R&D process and commercialization process. In this sense, the studies can consider these specific subprocesses to show a deeper vision of innovation performance evaluation. Moreover, this investigation uses the dataset from 2011 to 2014. New implications about increasing innovation performance might be acquired by using long-term data in the future.

Data Availability

The dataset is available from the corresponding author upon request.

Conflicts of Interest

There are no conflicts of interest regarding the publication of this article.

Acknowledgments

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