Evaluation on the Operational Efficiency of Health Institutions in China
Analysis Based on the Three-Stage DEA

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Abstract. The main purpose of this paper is to analyze the operational efficiency of China's health institutions in 2019 and the impact of environmental factors on efficiency, so as to provide references for policy-making. Relevant data having been obtained from *China Health Statistical Yearbook 2020* and *China Statistical Yearbook 2020,* the three-stage data envelopment analysis was adopted to eliminate environmental factors and random errors and to evaluate the efficiency of 31 health institutions in China. Three results are as follows: First, the technical efficiency, pure technical efficiency and scale efficiency of health institutions in China are 0.809, 0.931 and 0.871 respectively; second, the operational efficiency of central and eastern China is at the leading level in China while that of northwestern China falls behind, besides, northern China and northwestern China see an obvious imbalance of the operational efficiency; third, efficiency can be promoted by urban population density, total dependency ratio and financial allocation, while being hindered by regional GDP and case fatality rate. Finally, two conclusions were drawn: Environmental factors have an obvious effect on most areas; furthermore, a widespread waste of resource investment and the blind expansion of scale in medical institutions have existed in various regions. It is suggested that all regions should be adjusted according to local conditions after accurate analysis and scientific research and judgment to improve the operational efficiency.

Keywords: Health institutions · operational efficiency · three-stage DEA

1 Introduction

With the gradual improvement of China's basic medical system, people's sense of gain and satisfaction have been improved continuously, and the cause of health has developed to a certain extent. However, it should also be noted that the health resource in China is plagued by such problems as regional imbalance and low overall quality, and the service system and structural framework need to be further optimized and adjusted. By analyzing and evaluating the operational efficiency of health institutions in 31 provinces in 2019, this paper aims to provide decision-making reference for the development of health undertakings in China.

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2 Data Sources and Methods

2.1 Data Sources

The statistical data of health institutions and environmental factors in 31 provinces, autonomous regions and municipalities directly under the central government (excluding Hong Kong, Macao and Taiwan) in 2019 were obtained from the relevant report data of the National Health Commission and the National Bureau of Statistics of China. And the 31 provinces are divided into seven regions for discussion and analysis according to China's geographical division standard.

2.2 Research Methods

The three-stage DEA model proposed by Fried [4] was used to explore the operational efficiency of health institutions in China. In the first stage, with the help of the traditional DEA-BCC model and oriented by investment, the efficiency of each province is obtained based on the variable returns to scale.

In the second stage, the input redundancies obtained are taken as the explained variables and the selected environmental factors are taken as the explanatory variables. By using the stochastic frontier approach (SFA), the input redundancies are decomposed into three parts, namely the part affected by the environment, the part with low management efficiency, and the part with statistical noise.

In the third stage, the input data excluding environmental impact and statistical noise are brought into the DEA-BCC model again. At this time, the efficiency values are relatively accurate and can reflect the actual level of the operational efficiency of health institutions in various regions.

2.3 Index Selection

According to the research results of the literature review by reviewing and analyzing the similar literature [3], after excluding economic indicators [1], the number of visits and the number of discharges were selected as the output indicators; and the number of health institutions, the number of health personnel and the number of actual beds were selected as the input indicators. In the second stage of analysis, the environmental factors to be stripped out through the SFA model are also called external influencing factors [13]. Based on the characteristics of China's health resources, urban population density, regional GDP, total dependency ratio, case fatality rate and financial allocation are selected as environmental variables [6]. As can be seen from Table 1, there is an obvious regional imbalance in the allocation of health resources and a large gap in the capacity of health services in various regions in China.

Table 1. Descriptive statistics of output, input and environmental indicators

Indicators	Variables	Mean value	Standard deviation	Minimum value	Maximum value
Outputs	Number of visits (million)	281.286	222.491	16.343	891.798
	Number of discharges (million)	8.549	5.807	0.305	20.132
Inputs	Number of health institutions (thousand)	32.503	23.244	4.397	84.651
	Health personnel (thousand)	416.720	263.164	38.840	1,000.633
	Number of actual beds (thousand)	284.095	180.889	17.063	640.147
Environment variables	Urban population density (person / km^2)	3,008.100	1,121.606	1,137.000	5,498.000
	Regional GDP (100 million yuan)	31,687.870	25,848.694	1,698.000	107,987.000
	Total dependency ratio (%)	40.590	6.901	28.000	51.000
	Case fatality rate (%)	0.413	0.312	0.100	1.200
	Financial allocation (100 million yuan)	217.270	152.539	36.361	812.791

3 Results

3.1 Correlation Analysis of Input-Output Indicators

In order to ensure the mutual independence of different types of data, it is necessary to test the collinearity of the indicators before data calculation, that is, to judge the degree of mutual influence between the two. The Pearson correlation coefficient test results are shown in Table 2: The input and output indicators have a significant correlation at the level of 0.01, which meets the requirements of data directionality and can be calculated.

Table 2. Correlation Analysis of Input-Output Indicators

	Number of visits	Number of discharges	Number of health institutions	Number of health personnel	Number of actual beds
Number of visits	1				
Number of discharges	.864**	1			
Number of health institutions	.701**	.856**	1		
Number of health personnel	.936**	.958**	.858**	1	
Number of actual beds	.851**	.986**	.889**	.966**	1

Note: ** indicates that the correlation is significant at the level of 0.01 (two tailed).

3.2 Phase I DEA Analysis

The BCC model is constructed to analyze the operational efficiency of medical institutions in 31 provinces, and the results show that the average values of technical efficiency, pure technical efficiency and scale efficiency are 0.870, 0.922 and 0.946 respectively.

The results of the first stage can not reflect the actual operational efficiency of medical institutions. Therefore, it is a must to filter out the impact of environmental and random factors on the evaluation object in the traditional DEA model [2], so as to analyze the ineffective management more accurately.

3.3 Phase II SFA-Likelihood Analysis

The Frontier 4.1 software is adopted to decompose the inputs in the first stage, so that the adjusted decision-making unit faces the same external environment and the same level of luck [9]. The three input slack variables are analyzed in turn, and the results are shown in Table 3.

Through table comparison, the single side likelihood ratio test is greater than the critical value, so it is necessary to conduct stochastic frontier analysis on environmental variables. Most of the regression coefficients of environmental variables on input slack variables passed the student's t test, which is statistically significant, indicating that environmental factors have a significant impact on input redundancies. Gamma is close to 1, which shows that input redundancy is mainly affected by management inefficiency [5, 10], and random interference factors are negligible.

Table 3. Regression Analysis Results of SFA Model

Variables	Slack variable of the number of health institutions	Slack variable of the number of health personnel	Slack variable of the number of actual beds
Constant term	202.063*** (202.063)	48,512.645*** (48,512.646)	18,161.874*** (10,446.205)
Urban population density	0.371 (0.619)	-4.175*** (-29.457)	-5.309*** (-29.230)
Regional GDP	0.048 (1.154)	0.572** (2.397)	0.722** (2.536)
Total dependency ratio	-95.625*** (-95.303)	-1,413.648*** (-1,413.619)	-229.581*** (-88.601)
Case fatality rate	9.453*** (9.453)	23,895.275*** (23,895.275)	31,011.648*** (11,776.852)
Financial allocations	0.000 (-0.866)	-0.0122*** (-4.112)	-0.018*** (-5.380)
sigma-squared	284,612,240	3,693,415,900	1,727,868,900
gamma	1.000	1.000	1.000
Single side likelihood ratio test	25.533	12.735	15.356

Note: ** indicates $P < 0.050$, *** indicates $P < 0.010$; the results in brackets are the student's t-statistics of the estimated coefficients.

From the results, at the level of 1%, the urban population density and financial allocation have a negative correlation with slack variables of the health personnel and the actual beds, that is, increasing the environmental investment can narrow the gap between the ideal value and the actual value to improve the operation efficiency of medical institutions; the regional GDP at the level of 5% has a positive correlation with slack variables of the health personnel and the actual beds, that is, the increase of GDP will lead to the waste of health personnel and beds or the reduction of outputs. It shows that the development of the urban economy may lead to the blind expansion of hospital scale [8], resulting in a waste of resources, thus reducing the operational efficiency of health resources; the total dependency ratio and case fatality rate have obvious effects on the slack variables of various inputs, but have the opposite effect on improving the operational efficiency.

3.4 BCC Analysis Based on the Adjusted Inputs and Outputs

The adjusted input data are analyzed by the BCC model again. The results are shown in Table 4. Compared with the data of the first stage, the technical efficiency and scale efficiency decreased by 0.061 and 0.075 respectively, and the pure technical efficiency increased by 0.009. The decline of scale efficiency is the main reason for the decline

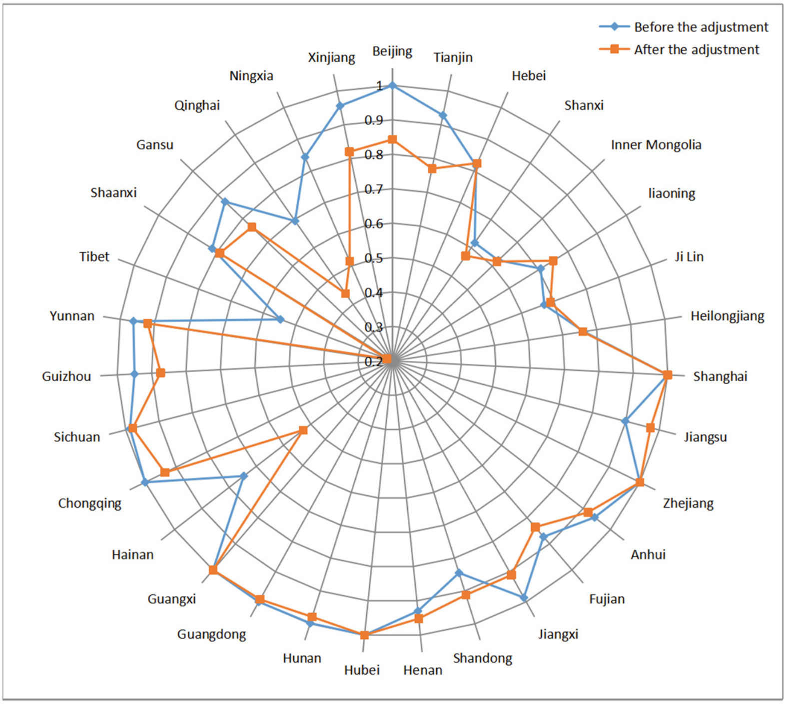

Fig. 1. Technical efficiency of China's provinces before and after the three-stage DEA adjustment

of technical efficiency, which reflects the blindness of the scale expansion of medical institutions in China.

Specifically, as shown in Fig. 1, the technical efficiency before and after the adjustment is 1. The provinces at the forefront of technology are Shanghai, Zhejiang, Hubei and Guangxi; the sharp decline in Qinghai and Tibet shows that environmental factors have the strongest impact on the operational efficiency of medical institutions in these provinces.

From the perspective of geographical region division, there are differences in technical efficiency among regions after adjustment. The technical efficiency of central and eastern China did not increase significantly after adjustment; northeastern China sees the most prominent rise, while northern, southern, northwestern and southwestern regions of China witness the most obvious decline, reflecting the overwhelming effect of environmental factors on the operational efficiency of health resources in most parts of the country.

Table 4. Efficiency of various regions in China before and after adjustment

	Technical efficiency		Pure technical efficiency		Scale efficiency	
	Before adjustment	After adjustment	Before adjustment	After adjustment	Before adjustment	After adjustment
The Northeast	0.713	0.733	0.741	0.839	0.962	0.874
The East	0.935	0.936	0.960	0.960	0.974	0.974
The North	0.797	0.726	0.823	0.836	0.969	0.871
The Central	0.976	0.977	1.000	1.000	0.976	0.977
The South	0.915	0.840	0.959	0.990	0.950	0.846
The Southwest	0.889	0.785	0.985	0.971	0.904	0.814
The Northwest	0.837	0.666	0.941	0.927	0.894	0.733
Mean value	0.870	0.809	0.922	0.931	0.946	0.871

4 Discussion

4.1 The Operational Efficiency of Medical Institutions in China is Generally Affected by Environmental Factors

From the regional perspective, the efficiency values of northern, southern, southwestern and northwestern regions of China decreased after adjustment, indicating that environmental factors played a positive role in the improvement of efficiency values in these regions; the allocation efficiency of health resources in central and eastern China has always been in the forefront before and after the adjustment, with a high level of management. It can provide pairing assistance [7] to the relatively backward western region to improve its technical level and service capacity.

The pure technical efficiency in northern and southern China increased by 0.013 and 0.031. At this time, environmental factors played a negative role, probably because of the excessive financial allocation and significant economic level which made the medical institutions more motivated to expand. It is suggested that when allocating health resources, all regions should first go through scientific calculation, accurately analyze the market [11], and establish an assessment system to timely adjust the unreasonable investment and reduce the waste of resources.

After the adjustment, the technical efficiency of northeastern China has been significantly improved, highlighting the negative impact of environmental variables; based on the changes of efficiency in various regions, it is suggested that medical institutions should shift more investment in scale expansion to the technical level in the development.

4.2 Different Environmental Factors Have Different Effects on Input Variables

Urban population density and financial allocation have a negative correlation between the number of health personnel and the number of actual beds. Similar to the research results of Xu Xiaofang et al. [12], this paper also found that the larger the population density is, the more conducive it is to improve the operational efficiency; to a certain extent, the financial allocation reduces the medical burden of residents, ensures people's demands for medical care, and promotes the use of health resources.

The total dependency ratio is negatively correlated with input redundancies. It indicates that with the increase of China's elderly population, the potential demand for medical services is increased and the utilization of various health resources can be promoted.

The case fatality rate and regional GDP are basically positively correlated with the slack variables of inputs, which hinders the improvement of operational efficiency. High case fatality rate may lead to the waste of input resources and reduce output benefits; in economically developed areas, it is more likely to expand medical institutions blindly, and it is more common for people to seek "a higher grade of medical treatment" than necessary, which is not conducive to improving the operational efficiency on the whole.

4.3 There Are Obvious Differences in the Operational Efficiency of Medical Institutions in Different Provinces Within a Region

The adjusted technical efficiency values of Beijing and Hebei are 0.843 and 0.825 respectively, which are higher than the national average level. However, due to the large difference between the technical efficiency of Tianjin, Shanxi and Inner Mongolia and that of the national average level, the overall operational efficiency of northern China is reduced, and the same problem also exists in northwestern China.

In view of the differences in the operational efficiency of health resources within a region, we can gradually fill the gap through exchanges and cooperation as well as complementary advantages. For example, provinces with high technical efficiency like Beijing and Xinjiang can promote the co-construction and sharing of medical achievements by sharing the digital dividends of medical reforms, and the service interconnection of "cloud hospital" can promote the improvement of the overall efficiency of the region with the aid of informatization.

5 Conclusions

Overall, the operational efficiency of medical institutions in China is generally affected by environmental factors. The waste of resource investment and blind expansion of medical institutions in various regions are common. It is suggested that all regions make adjustments according to local conditions after precise analysis and scientific analysis to improve operational efficiency.

Specific to each province, different environmental factors have different effects on input variables. There are obvious differences in the operational efficiency of medical institutions in different provinces within a region. In view of the differences in the operation efficiency of health resources within the region, the gap can be gradually bridged through exchanges and cooperation to complement each other's advantages.

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