Risk Management and Healthcare Policy

Dovepress
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ORIGINAL RESEARCH

Enhancing Health Productivity in China: A Decade of Measurement and Regional Insights (2010–2020)

Dechen Kong, Nan Jiang, Xiaomin He, Jing Yuan, Qing Du, Wu Lian

Health Management School of Binzhou Medical University, Yantai, Shandong, People's Republic of China

Correspondence: Qing Du; Wu Lian, Email duqing1998@hotmail.com; 744592475@qq.com

Background: Enhancing health productivity is a pressing priority to promote the Healthy China Initiative. This study aims to assess the efficiency of health production and to analyze the disparities in efficiency across regions.

Methods: A multi-dimensional approach is used to assess the health efficiency of 31 provinces in China over the period 2010 to 2020. The analysis incorporates the conventional BCC model, the super-efficient SBM model, and the Malmquist index model within the framework of DEA modeling. And using the Dagum Gini coefficient to further analyze the differences in health productivity of China.

Results: The BCC model calculated China's comprehensive health production efficiency in 2020 to be 0.732. The SBM model assessed the average health productivity value among China's provinces in 2020, revealing Guangdong as the highest (2.276) and Qinghai as the lowest (0.351). The average value of China's Malmquist Index from 2010 to 2020 was 1.002, indicating a slight overall improvement in health production efficiency. Furthermore, the score of technological change and technological efficiency change in five provinces were more than 1. Gini coefficient had obvious downward trend from 2010 to 2020, and there was a lower level in the northeastern (0.055) and eastern (0.0989) regions.

Conclusion: Though the whole health productivity of China has been on the rise, health production efficiency in many provinces still needs to be improved. Inequities in health services provision persist, particularly between the eastern and western regions. The government should play a significant role in establishing standardized criteria for regular evaluation of health production efficiency levels. It's suggested to utilize digital health technologies to facilitate the exchange of information among different regions in China, thereby fostering collaborative efforts to improve overall health outcomes.

Keywords: health productivity, 31 provinces of China, measurement

Introduction

In the report of the 20th National Congress of the Communist Party of China, General Secretary Xi Jinping emphasized the significance of people's health as a key indicator of national prosperity and strength. He called it is imperative to enhance the national health policy, prioritize the protection of people's health in the strategic development agenda, and ensure the provision of comprehensive and continuous health services to the population by 2030. With the development of the country and the increase in government investment, the equity of health in China has been improving. From 2010 to 2020, China was projected to experience a notable rise in average life expectancy from 74.83 years to 77.93 years. Additionally, the maternal mortality rate (MMR) was decreased from 30.0 per 100,000 to 16.9 per 100,000, while the infant mortality rate was dropped from 13.1‰ to 5.4‰. However, the level of health outputs depends more on the increase in health productivity, in addition to health inputs.[1] For example, China's life expectancy is projected to be 78.6 years in 2024. In contrast, some developed countries, such as Japan, Switzerland, and South Korea, have already achieved life expectancy exceeding 83 years, highlighting a significant disparity between China and these nations. The average MMR in OECD countries was 10.9 per 100,000 in 2020. Australia and New Zealand have decreased MMR to 4 per 100,000. This indicates that there remains considerable

Received: 5 November 2024
Accepted: 20 February 2025
Published: 13 March 2025

room for improvement in China's maternal health outcomes. Some problems still exist, such as regional disparities in the distribution of medical resources, notable structural issues, and inadequate management systems in the healthcare sector in China.[2,3] These challenges, if left unaddressed, could greatly hinder the progress of the "Healthy China 2030" initiative. Analyzing the level of health service efficiency through scientific measurements and studying inter-regional differences can offer valuable insights for government departments to enhance the efficiency of health services and optimize the health service system. This has significant practical implications for advancing the coordinated development of China's health, economy, and society.

Both domestic and international scholars have primarily concentrated on healthcare resource allocation and the evaluation of healthcare service efficiency.[4–7] Significant progress has been made in measuring health service efficiency.[5,8,9] However, the improvement is still needed in uncovering the extent of regional differentiation. Many domestic scholars commonly utilize health demand model by Dr. Grossman in their research. For studies in China, methods are often employed to assess the efficiency of health output in various regions, such as Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and the Malmquist Index. These studies aimed to investigate the disparities in efficiency across different areas.[10–13] Our study examines the health productivity of 31 province from 2010 to 2020, based on the policy framework of the "Healthy China 2030" initiative. Utilizing national panel data, the DEA traditional BCC model is employed for cross-sectional analysis year by year, while the Malmquist productivity change index model is used for vertical inter-period analysis. Additionally, Dagum's Gini coefficient and its decomposition are utilized to investigate inter-regional differences. The study aims to offer insights for enhancing health equity across regions in China and advancing the development of a healthier China.

Methods

Efficiency Measurement Variables and Data Sources

This study examines the health productivity levels in China and explores the regional disparities based on economic divisions. The data source for this study consists of panel data from China's 31 provinces spanning from 2010 to 2020. Data sources include the China Statistical Yearbook, China Public Health Statistical Yearbook, as well as the statistical yearbooks of each province from 2010 to 2020. Table 1 provides detailed information on the variables selected for this study.

Table 1 Specifics of the Variables Selected for the Measurement of Health Productivity

Variable Category	Variable Name	Concrete Explanation	Unit
Output variables	Maternal mortality rate	Maternal deaths per 100,000 live births	/100,000
	Perinatal mortality rate	The ratio of neonatal deaths to live births from 28 weeks of gestation or birth weight ≥1000 grams to 7 days after delivery	‰
	Incidence of Category A and B infectious diseases	Number of cases of legally reported infectious diseases of categories A and B per 100,000 population in an area in a given year	/100,000
Input variables	Health workers per 1000 population	Number of health workers/population x 1000	/1000
	Number of beds in health facilities per 1000 population	Number of beds in health-care facilities/population x 1000	/1000
	Health costs per capita	The ratio of total health costs in a given year to the average population in the same period	Yuan

Health Output Variables

Many studies now utilize indicators such as average life expectancy, maternal mortality rate, perinatal mortality rate, disease morbidity, and disability-adjusted life expectancy to measure health outcomes.[1] However, due to difficulties in data collection in certain provinces, obtaining comprehensive data on average life expectancy and the prevalence of chronic diseases in each province over the years is not available. The selection of typical diseases for calculating disease incidence significantly affects the accuracy of measuring population health levels. Variations in disease prevalence across regions pose challenges in disease selection. And some studies in China use the total number of person-years of survival as an indicator of population health, as demonstrated by Li et al.[11,14] But due to limitations in China's statistical data, the results of the indicators obtained are relatively basic. So this study selects the maternal mortality rate, perinatal mortality rate, and incidence rate of infectious diseases as health output variables to reflect the population's health level, considering the accessibility and quality of the indicator data. Based on the limitation that the DEA model is difficult to deal with negative output data, this study positively normalizes the three output variables (all taking the inverse) in order to eliminate heterogeneity.

Health Input Variables

Health production inputs are typically evaluated based on three key elements: human resources, financial resources, and material resources.[15] For this study, the following three indicators have been chosen as variables to measure the efficiency of health production inputs: the ratio of health technicians per 1000 population, the ratio of beds in health institutions per 1000 population, and health expenditure per capita.

Model Selection and Research Assumptions

Since its introduction in 1978 by Charnes et al, the Data Envelopment Analysis (DEA) method for calculating relative efficiency has undergone continuous improvement and innovation.[16] There are three main types of DEA models: Charnes-Cooper-Rhodes (CCR), Banker-Charnes-Cooper (BCC), and DEA-Malmquist index model.[17] The CCR, BCC, and super-efficiency Slack-Based Measure (SBM) models are cross-sectional annual analytical models used for comparing Decision Making Units (DMUs) within a single period, whereas the DEA-Malmquist index model is a vertical inter-period analytical model used for comparing DMUs across different periods. In the horizontal annual analysis model, CCR is used to assess the relative efficiency of the decision unit assuming fixed-scale remuneration. The CCR model allows for the calculation of the technical efficiency value of the decision unit. The BCC model does not rely on the fixed scale remuneration assumption, making it suitable for measuring the relative efficiency of the decision unit under various scale remuneration conditions. The BCC model provides values for technical efficiency, pure technical efficiency, and scale efficiency through its calculations. The super-efficiency SBM model enables a ranked comparison of the relative efficiency values of all DMUs, while the longitudinal cross-period analysis DEA-Malmquist index model assesses how and why the productivity of DMUs changes over time. The CCR model is not suitable for the variable reward scale of health level improvement. Therefore, this study will utilize the BCC model and the super-efficient SBM model to evaluate health production efficiency in 2020. In addition, the DEA-Malmquist index model will be used to assess efficiency changes from 2010 to 2020. This study aims to ensure rigor, scientific validity, and comprehensiveness in the evaluation process. The specific conditions for models application can be seen in Table 2.

Table 2 Introduction of Models

Model	Applicable Conditions
CCR model	Fixed-scale remuneration
BCC model	Variable-scale remuneration
DEA-Malmquist index model	Measure dynamics of the productivity of the DMUs over time
Super-efficiency SBM model	Ranked comparison of the relative efficiency values of all DMUs

Horizontal Annual Analysis Model

BCC model with variable returns to scale

The input-oriented BCC model:

$$\text{Min } \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$\text{Subject to } \sum_{t=1}^{n} \lambda_t X_{it} - \theta_0 X_{i0} + s_i^- = 0, i = 1, 2, \ldots\ldots m$$

$$\sum_{t=1}^{n} \lambda_t Y_{rt} - Y_{r0} + s_t^+ = 0, r = 1, 2, \ldots\ldots s$$

$$\sum_{t=1}^{n} \lambda_t = 1$$

$$\lambda_{t'} s_i^-, s_t^+ \geq 0$$

The θ_0 denotes the pure technical efficiency of the evaluated DMUs, Xit is i th input of the t th DMU, where Yrt represents the weight for the t th DMU,s_i^- represents the variance in the difference of i th input, and s_t^+ represents the variance in the difference of the r th in output. When $\theta_0 = 1$, the DMU is relatively pure technical efficiency for DEA, $s_i^- = s_t^+ = 0$; where θ_0<1, the DMU is ineffective in terms of pure technical efficiency, and it is possible to derive the variance of the difference between the input and output terms concerning the frontier surface, s_i^-, s_t^+.

Where $\theta_0 = 1$, $s_i^- = s_t^+ = 0$, the j th DMU is relatively efficient for DEA, which means the j th DMU output is optimized, and the technical efficiency of the DMU is the most efficient;

Where $\theta_0 = 1$, $s_i^- \neq s_t^+ \neq 0$, the j th DMU is weakly effective for DEA, it means with constant inputs, the DMU can increase outputs s_t^+;

Where θ_0<1, the DMU is Non-DEA valid or DEA invalid, which means the DMU increased outputs with no change in inputs.

The output-oriented BCC model:

$$\text{Max. } \theta_0 + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$\text{Subject to } \sum_{t=1}^{n} \lambda_t X_{it} - X_{i0} + s_i^- = 0, i = 1, 2, \ldots\ldots m$$

$$\sum_{t=1}^{n} \lambda_t Y_{rt} - \theta_0 Y_{r0} + s_t^+ = 0, r = 1, 2, \ldots\ldots s$$

$$\sum_{t=1}^{n} \lambda_t = 1$$

$$\lambda_{t'} s_i^-, s_t^+ \geq 0$$

The expression refers to the same as the input orientation.

Variable-size super-efficiency models

It is modeled as:

$$\left(\begin{array}{c} s.t. \\ \sum_{j=1, j\neq k}^{n} \lambda_j X_{ij} \leq \theta X_{ik} \\ \sum_{j=1, j\neq k}^{n} \lambda_j Y_{ij} \leq Y_{rk} \\ \sum_{j=1, j\neq k}^{n} \lambda_j = 1 \\ \lambda \geq 0 \\ i = 1, 2, \ldots m; r = 1, 2, \ldots\ldots q; j = 1, 2, \ldots\ldots nj \neq k); \end{array}\right)$$

The expression designation is the same as the BCC model.

Longitudinal Intertemporal Analysis Models

Malmquist Index of productivity change model definition

The DEA cross-sectional annual analysis describe above can assess the production efficiency of DMUs within a single period, but it is limited in to analyze efficiency and productivity changes over multiple periods. Farell et al introduced the DEA-Malmquist index model as a measure of productivity change. The index calculates the pooled average of productivity indices for periods t and t+1, enabling the evaluation of productivity changes in DMUs over time. This model facilitates further analysis of the causes of productivity changes.

Productivity is measured by the ratio of total output to weighted average inputs, with evaluation indicators such as partial factor productivity (PFP) and total factor productivity (TFP). PFP is the ratio of output to a single input, while TFP measures the growth rate of output from all factors of production excluding labor and capital.

Malmquist productivity change indicators are modeled as:

$$M_0^{t+1} = \left[\frac{D^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D^t\left(x_0^t, y_0^t\right)} \times \frac{D^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D^{t+1}\left(x_0^t, y_0^t\right)}\right]^{\frac{1}{2}}$$

The $D^t\left(x_0^t, y_0^t\right)$ and $D^{t+1}\left(x_0^t, y_0^t\right)$ represent the output distance functions for period t and period t+1, respectively. The $D^{t+1}\left(x_0^t, y_0^t\right)$ denotes the output distance function when the inputs and outputs of the n DMUs in period t+1 are used as a reference ensemble to measure the outputs of a particular input in period t. Similarly, the $D^t\left(x_0^{t+1}, y_0^{t+1}\right)$ denotes the output distance function when the inputs and outputs of the n DMUs in period t are used as a reference ensemble to measure the outputs of a particular input in period t. If the value of $M_0^{t+1}>1$, it indicates an increase in productivity. Conversely, if $M_0^{t+1}<1$, it signifies a decrease in productivity. Lastly, if $M_0^{t+1} = 1$, it denotes no change in productivity.

Decomposition of Malmquist's index model of productivity change

The DEA-Malmquist index model decomposes Total Factor Productivity Change (TFPC) into the product of Technical Change (TC) and Technical Efficiency Change (TEC). Assuming variable returns to scale, TC can be further broken down into Pure Technical Efficiency Change (PTEC) and Scale Efficiency Change (SEC), expressed as TC = PTEC x SEC.

Results

Descriptive Analysis of Health Input and Output Indicators

Total National Health Inputs and Outputs

As illustrated in Figure 1, between 2010 and 2020, there was a consistent increase in various health input indicators in China. The number of health technicians per 1000 population rose from 4.39 in 2010 to 7.57 in 2020; the number of health facility beds per 1000 population increased from 3.58 to 6.46; and the health cost per capita escalated from 1490.1 yuan to 5111.1 yuan. The growth trend fluctuated, with the most rapid increase seen in health costs per capita, followed by the number of health facility beds per 1000 population, and the slowest annual growth observed in the number of health technicians per 1000 population.

As shown in Figure 2, from 2010 to 2020, there was a significant improvement in the health status of China's residents. The MMR decreased from 30.0/100,000 in 2010 to 16.9/100,000 in 2020, the perinatal mortality rate dropped from 7.02‰ to 4.14‰ in 2020, and the incidence rate of Class A and B infectious diseases decreased from 283.69/100,000 to 190.36/100,000. The pace of reduction varied, with the MMR declining the fastest, followed by the perinatal mortality rate, and the incidence rate of infectious diseases of types A and B showing the slowest decline.

Descriptive Analysis of Health Input-Output Indicators by Region

According to the economic regional division method released by China's National Bureau of Statistics in 2011, China's 31 provinces were categorized into four regions: eastern, central, western, and northeastern.[18] As shown in Figure 3, it was evident that the number of health technicians per 1000 population and the level of investment in health costs per capita in the eastern and northeastern regions surpassed the national average. The disparity between the central and western regions and the national average has been gradually decreasing over the years. The number of beds in health institutions per 1000 population in the western and northeastern regions was higher than the national average. The difference between the central region and the national average had been narrowing year by year. After 2012, the eastern region has a lower number of beds

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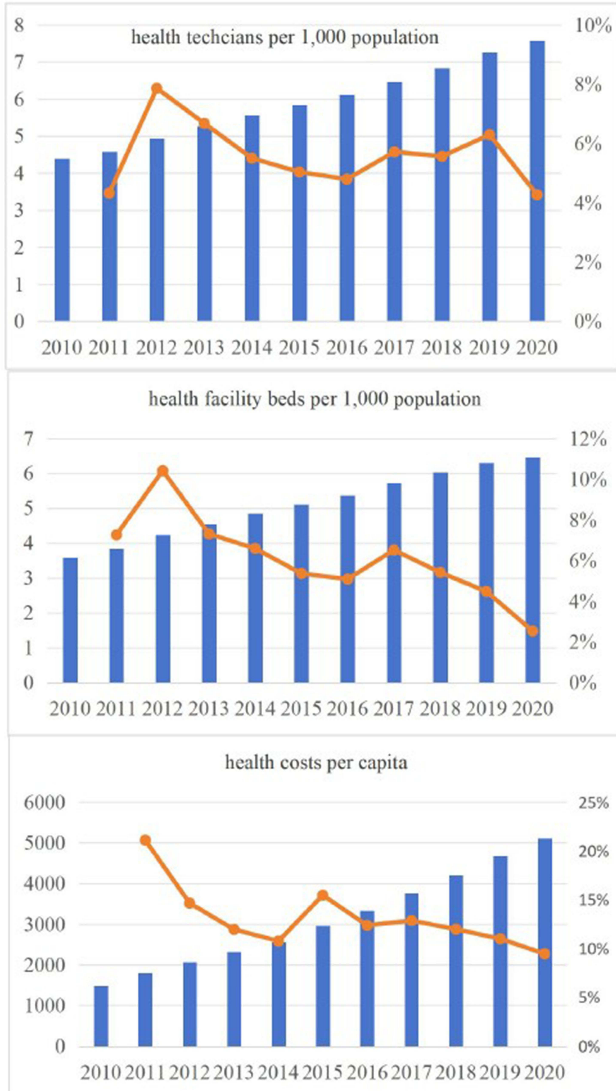

Figure 1 Number of Health Technicians per 1000 Population, Number of Beds in Health Facilities per 1000 Population, Health Costs per Capita and Their Trends, 2010–2020. This composite graph presents three key health-related metrics over the decade from 2010 to 2020. The first panel displays the number of health technicians per 1000 population, the second panel illustrates the number of health facility beds per 1000 population, and the third panel depicts health costs per capita. Each metric is represented by both a bar graph (in blue) and a line graph (in Orange), facilitating the visualization of absolute values and percentage changes over time, respectively. The data reveals fluctuations in the number of health technicians and beds, alongside a general increasing trend in health costs per capita. This visualization offers valuable insights into the developments and challenges faced by the healthcare sector over the past decade.

compared to the national average. Health costs per capita in the eastern and northeastern regions were higher than the national average. After 2016, the northeastern region has been growing slowly and was below the national average. However, it was expected to reach a level close to the national average by 2020. The western region was projected to be roughly at the same level as the national average. The central region remained below the national average though it experienced a gradual increase in health costs per capita year by year. The findings are presented in Figure 3.

As shown in Figure 4, MMR in the eastern, central, and northeastern regions was lower than the national average, and the gap between western region and the national average is gradually closing. Perinatal mortality rates are below the national average in the eastern and central regions. The incidence of infectious diseases of category A and B rates in the eastern and northeastern regions was lower than the national average with a widening gap. The incidence of infectious diseases of category A and B rates in the western and central regions was higher than the national average, but this gap has been narrowing annually.

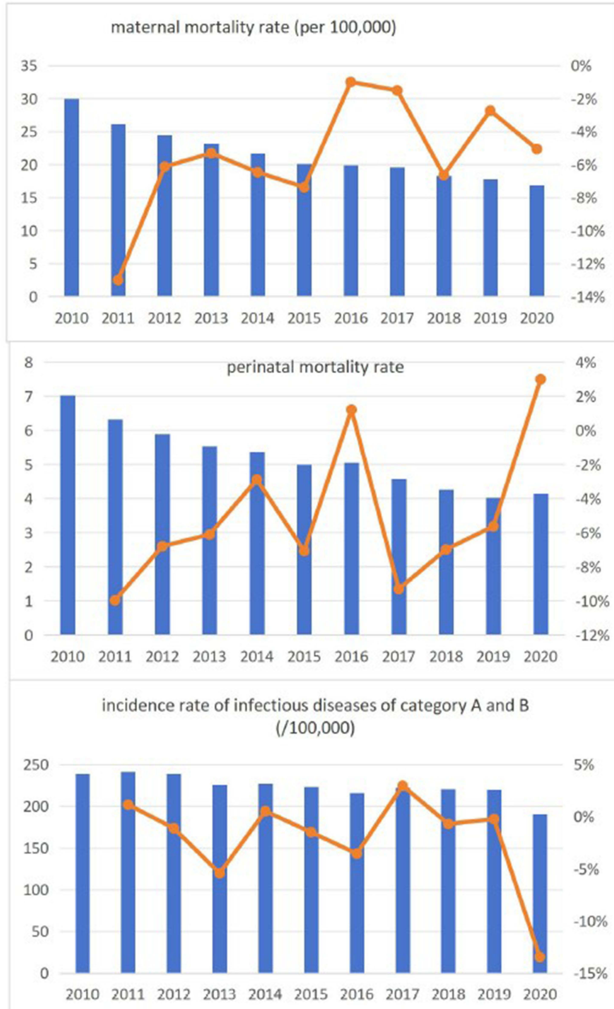

Figure 2 Maternal Mortality Rate, Perinatal Mortality Rate, Incidence Rate of Category A and B Infectious Diseases and Their Trends, 2010–2020. This composite graph presents three critical health metrics over the decade from 2010 to 2020: 1. **Maternal Mortality Rate (per 100,000)** - The first panel depicts the maternal mortality rate, represented by blue bars, with an Orange line indicating the percentage change. The data reveals a general decline in maternal mortality over the years. 2. **Perinatal Mortality Rate** - The second panel illustrates the perinatal mortality rate, utilizing blue bars for absolute values and an orange line to represent percentage change. This metric also demonstrates a general downward trend, albeit with some fluctuations. 3. **Incidence Rate of Infectious Diseases of Category A and B (per 100,000)** - The third panel depicts the incidence rate of infectious diseases classified as A and B. The blue bars represent the incidence rate, while the orange line indicates the percentage change. This metric exhibits fluctuations, with a notable decline observed towards the end of the decade. Each panel includes a secondary y-axis on the right to display the percentage change, enhancing the clarity of the trends over time. This visualization aids in understanding the progress and challenges in public health over the past decade.

Cross-Sectional Annual Analysis of Traditional BCC Model

This study focuses on improving health production efficiency by increasing output and adopts an output-oriented approach in the model analysis. The DEAP2.1 software is utilized for data analysis, with the output-oriented BCC model selected to assess health production efficiency in China in 2020. Recognizing the challenge of dealing with negative output data in DEA models, this study normalized three output variables by taking the inverse number to address heterogeneity. The findings are presented in Figures 5, 6 and Table 3.

In 2020, the average comprehensive efficiency of health production in China was 0.732. In China, 17 provinces were below this average level. The average pure technical efficiency stood at 0.831, with 14 provinces falling below this mark. Additionally, the average scale efficiency was 0.886, with 10 provinces below this average. The comprehensive efficiency varied from 0.334 to 1, highlighting significant disparities in health production efficiency among Chinese provinces. 6 provinces have achieved a comprehensive efficiency of 1, namely Beijing, Shanghai, Jiangsu, Zhejiang, Jiangxi, and Jilin, accounting for 19.35% of the total. This suggests that these provinces have effectively utilized their

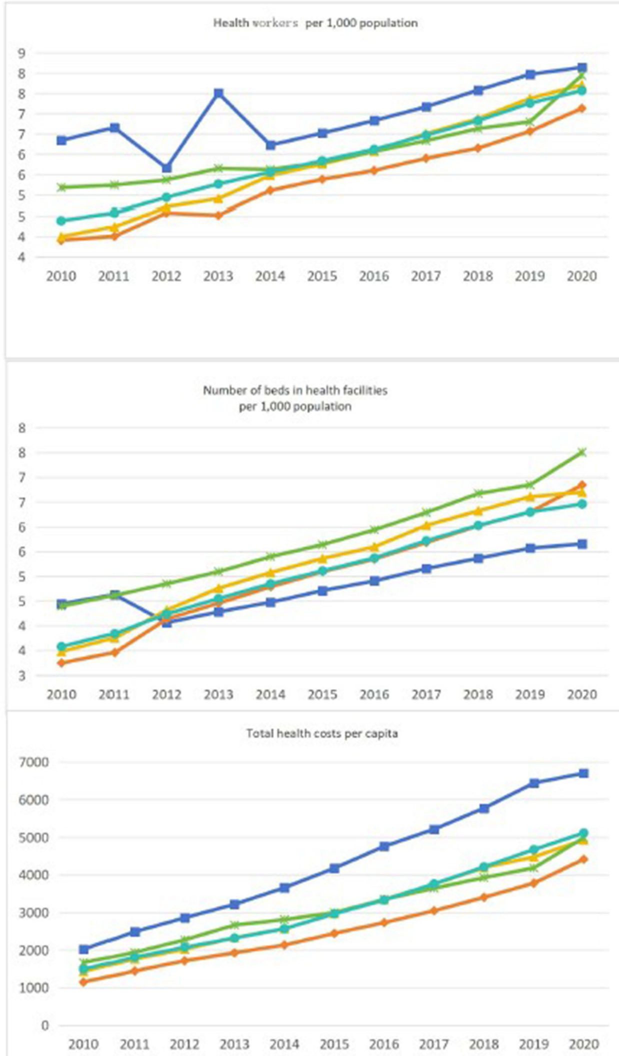

Figure 3 Health Workers, Number of Beds in Health Facilities, Total Health Costs by Region, 2010–2020. This composite line graph presents three key health metrics across five regions in China from 2010 to 2020:1. **Health Workers per 1000 Population** - The first panel displays the number of health workers per 1000 population. The lines represent different regions: Eastern Region (blue), Central Region (Orange), Western Region (yellow), Northeast Region (green), and Nationwide (cyan). The data indicates a steady increase in health workers across all regions over the decade.2. **Number of Beds in Health Facilities per 1000 Population** - The second panel illustrates the number of beds in health facilities per 1000 population. Similar to the first panel, the lines represent the same regions. This metric also shows a consistent upward trend, reflecting improvements in healthcare infrastructure.3. **Total Health Costs per Capita** - The third panel depicts the total health costs per capita. The lines again represent the five regions. This metric shows a significant increase over the years, indicating rising healthcare expenditure. Each panel includes a legend to distinguish between the regions, and the x-axis represents the years from 2010 to 2020. The y-axis in each panel is scaled to the respective metric, facilitating a clear comparison of trends within each category. This visualization provides valuable insights into the development and resource allocation in the healthcare sector across different regions in China over the past decade.

health resources and have achieved an optimal level of health production efficiency. In contrast, Qinghai, Xinjiang, and Tibet have lower efficiency levels with 0.334, 0.351, and 0.370, these 3 provinces all locate in the western region. It indicates that the health productivity should be improved in further in western region.

13 provinces exhibited effective pure technical efficiency, accounting for 41.94% of the total. It suggests that these provinces were utilizing technology to its fullest potential within their current scale, indicating high levels of management and achieving maximum output with fixed inputs. Among these provinces, Tianjin, Hebei, Fujian, Guangdong, Henan, Guangxi, and Tibet stood out with a pure technical efficiency score of 1. However, their comprehensive efficiency fell below 1, indicating that their DEA was ineffective due to scale inefficiency. These 7 DMUs were deemed weakly effective in DEA. There were 18 provinces where the DEA was not effectively utilized, highlighting the need for enhanced utilization of health resources. Tibet, Guangxi, and Guizhou ranked the lowest in terms of health service

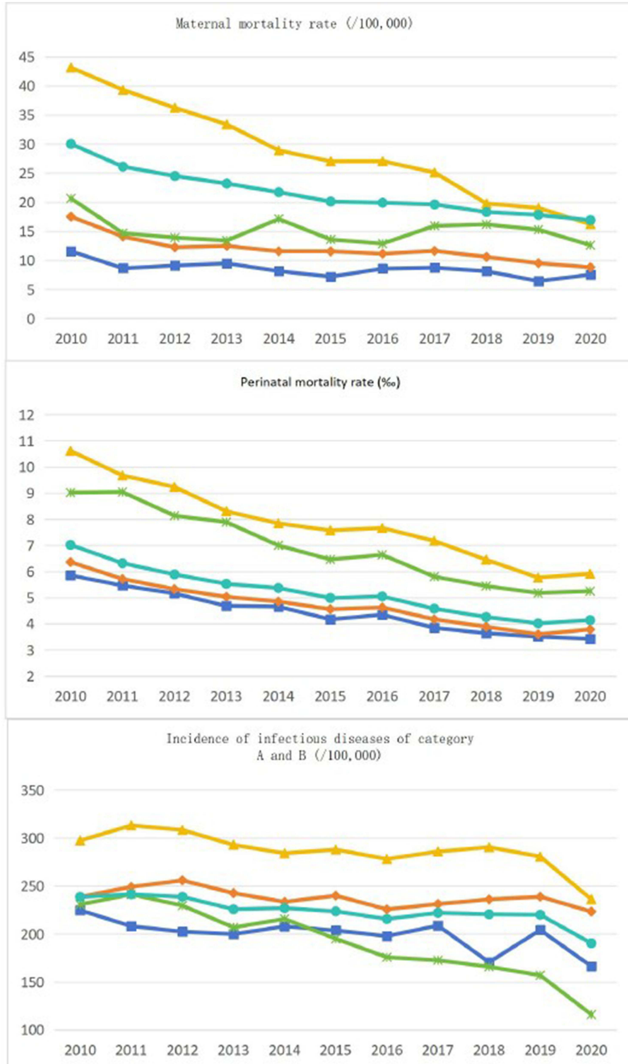

Figure 4 Maternal Mortality Rate, Perinatal Mortality Rate, Incidence of Infectious Diseases of Category A and B by Region, 2010–2020. This composite line graph presents three critical health metrics across five regions in China from 2010 to 2020: 1. **Maternal Mortality Rate (per 100,000)** - The first panel displays the maternal mortality rate, with lines representing different regions: Eastern Region (blue), Central Region (Orange), Western Region (yellow), Northeast Region (green), and Nationwide (cyan). The data indicates a general decline in maternal mortality across all regions over the decade. 2. **Perinatal Mortality Rate (%)** - The second panel illustrates the perinatal mortality rate, with lines again representing the same regions. This metric shows a consistent downward trend, reflecting improvements in maternal and infant health. 3. **Incidence of Infectious Diseases of Category A and B (per 100,000)** - The third panel depicts the incidence of infectious diseases categorized as A and B, with lines representing the five regions. This metric exhibits fluctuations but demonstrates a general downward trend towards the end of the decade. Each panel includes a legend to distinguish between the regions, while the x-axis represents the years from 2010 to 2020. The y-axis in each panel is scaled to the respective metric, facilitating a clear comparison of trends within each category. This visualization offers insights into the progress and challenges in public health across different regions in China over the past decade.

utilization, suggesting that these areas were not fully maximizing the available technology and resources. There is a clear necessity to enhance health investments and optimize the management of health service organizations to improve overall health productivity.

There were 6 provinces with optimal scale efficiency (equal to 1), making up 19.35% of the total. It suggests that these 6 provinces had currently achieved the ideal scale and they were functioning at the right size, with no need to adjust their scale or change the state of returns to scale. Among the remaining 25 provinces where scale efficiency was not effective, 23 provinces (92%) exhibited increasing returns to scale. This suggests that the increase in regional outputs was greater than the increase in inputs, indicating that increasing inputs would lead to higher outputs, ultimately improving efficiency. Hubei was the only province that exhibited diminishing returns to scale, where the increase in inputs surpassed

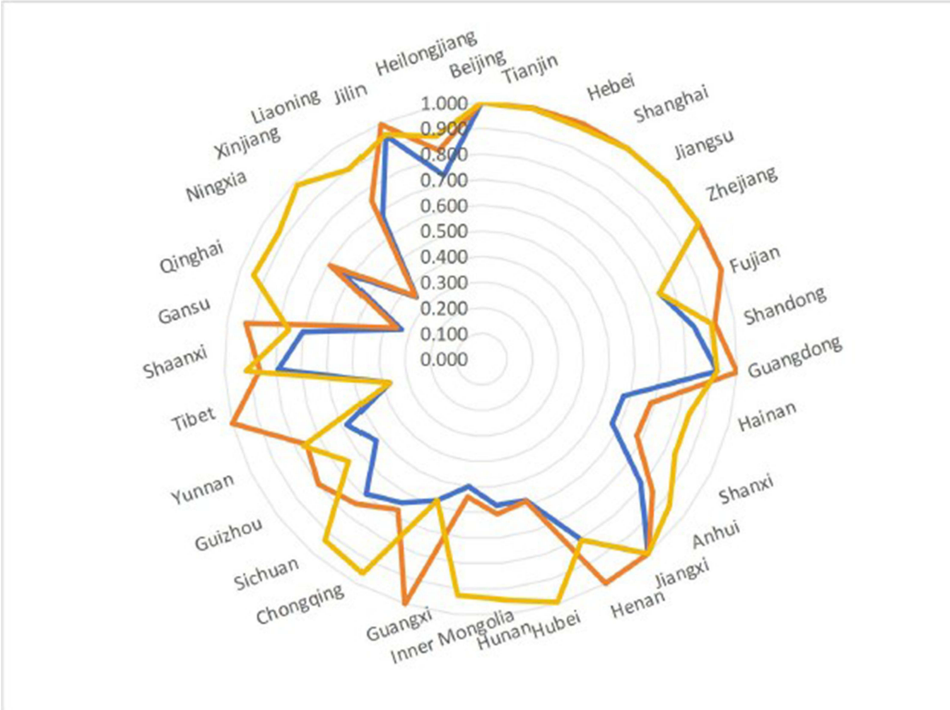

Figure 5 Radar chart of provincial health productivity in China, 2020. This radar chart compares the performance of 31 provinces across various dimensions. The legend delineates the data series for each group, with distinct colors representing different categories: TE (Technical Efficiency, blue), PTE (Pure Technical Efficiency, Orange), and SE (Scale Efficiency, yellow). A total of 13 provinces demonstrated effective pure technical efficiency, accounting for 41.94% of the overall total. Among these, Tianjin, Hebei, Fujian, Guangdong, Henan, Guangxi, and Tibet achieved a pure technical efficiency score of 1. However, their comprehensive efficiency scores fell below 1, indicating that their Data Envelopment Analysis (DEA) was ineffective due to scale inefficiencies. These seven Decision-Making Units (DMUs) were classified as weakly effective in DEA. Furthermore, 18 provinces exhibited ineffective utilization of DEA, highlighting the need for improved health resource allocation. Notably, Tibet, Guangxi, and Guizhou ranked the lowest in terms of health service utilization.

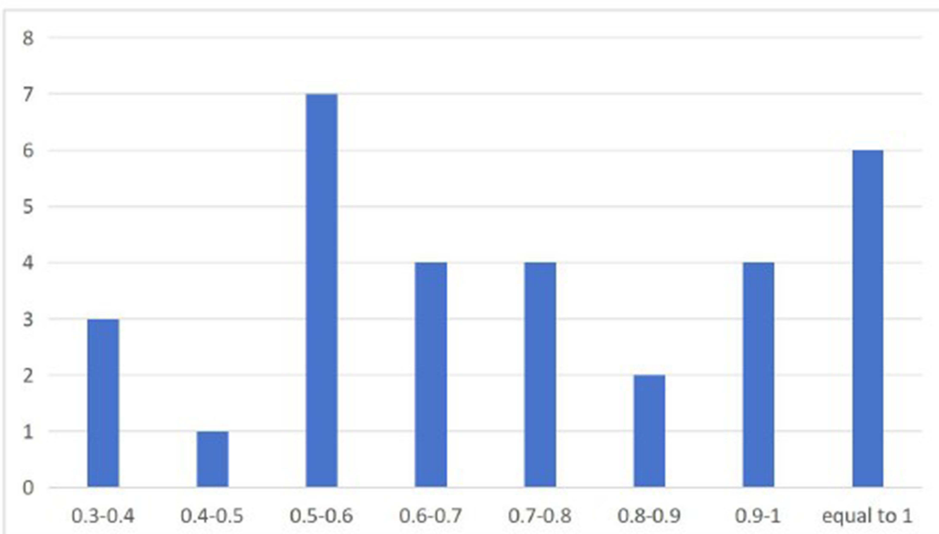

Figure 6 Distribution of Comprehensive Efficiency in China's Provinces in 2020. This bar chart illustrates the distribution of comprehensive efficiency (TE) among China's provinces for the year 2020. The x-axis represents different efficiency ranges, while the y-axis shows the number of provinces falling within each range. The efficiency is categorized into seven bins: 0.3–0.4, 0.4–0.5, 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9, 0.9–1, and equal to 1. The chart reveals that the majority of provinces have an efficiency score within the 0.5–0.6 and 0.9–1 ranges, indicating a significant disparity in efficiency levels across different regions. This visualization helps in understanding the variability in comprehensive efficiency among provinces and identifying areas for potential improvement.

Table 3 Health Productivity in China's Provinces, 2020

Decision Making Unit	Combined Efficiency	Pure Technical Efficiency	Scale Efficiency	Return to Scale Status	DEA Active State
Beijing	1.000	1.000	1.000	–	Validity
Tianjin	0.997	1.000	0.997	irs	Weakly effective
Hebei	0.983	1.000	0.983	irs	Weakly effective
Shanghai	1.000	1.000	1.000	–	Validity
Jiangsu	1.000	1.000	1.000	–	Validity
Zhejiang	1.000	1.000	1.000	–	Validity
Fujian	0.741	1.000	0.741	irs	Weakly effective
Shandong	0.840	0.923	0.910	irs	Null
Guangdong	0.923	1.000	0.923	irs	Weakly effective
Hainan	0.574	0.683	0.840	irs	Null
Shanxi	0.569	0.676	0.842	irs	Null
Anhui	0.787	0.846	0.930	irs	Null
Jiangxi	1.000	1.000	1.000	–	Validity
Henan	0.807	1.000	0.807	irs	Weakly effective
Hubei	0.577	0.581	0.993	drs	Null
Hunan	0.573	0.607	0.944	irs	Null
Inner Mongolia	0.499	0.540	0.925	irs	Null
Guangxi	0.577	1.000	0.577	irs	Weakly effective
Chongqing	0.641	0.672	0.953	irs	Null
Sichuan	0.693	0.744	0.931	irs	Null
Guizhou	0.520	0.798	0.651	irs	Null
Yunnan	0.581	0.755	0.769	irs	Null
Tibet	0.370	1.000	0.370	irs	Weakly effective
Shaanxi	0.790	0.862	0.916	irs	Null
Gansu	0.701	0.927	0.756	irs	Null
Qinghai	0.334	0.354	0.944	irs	Null
Ningxia	0.642	0.691	0.929	irs	Null
Xinjiang	0.351	0.356	0.985	irs	Null
Liaoning	0.678	0.753	0.901	irs	Null
Jilin	1.000	1.000	1.000	–	Efficiently
Heilongjiang	0.948	0.995	0.953	irs	Null
Average	0.732	0.831	0.886		

Table 4 Summary of Provincial Health Services Productivity Classification in China, 2020

DEA Effectiveness	Return to Scale Status	Decision Making Unit
DEA effective	Fixed remuneration for size	Beijing, Shanghai, Jiangsu, Zhejiang, Jiangxi, Jilin
DEA weakly effective	Increasing returns to scale	Tianjin, Hebei, Fujian, Guangdong, Henan, Guangxi, Tibet
	Diminishing returns to scale	–
DEA null and void	Increasing returns to scale	Shandong, Hainan, Shanxi, Anhui, Hunan, Inner Mongolia, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Liaoning, Heilongjiang
	Diminishing returns to scale	Hubei

the increase in outputs. Maybe adding more inputs will not significantly increase outputs due to the existing high input levels. The health productivity classification of each province can be found in Table 4.

The average efficiency was calculated for comprehensive efficiency, pure technical efficiency, and scale efficiency, as illustrated in Figure 7. The scale efficiencies of the eastern, central, western, and northeastern regions of China were all above 0.8, indicating that the health services in these regions were operating at an optimal scale. The eastern and northeastern regions exhibited higher comprehensive efficiency and pure technical efficiency compared to the central and western regions, which still showed significant disparities in both aspects when compared to the former.

Cross-Sectional Annual Analysis of Super-Efficient SBM Model

Building upon the traditional BCC model, the health production efficiency of Chinese provincial DMUs in 2020 was examined. However, due to all DMUs achieving a technical efficiency score of 1.000 in DEA analysis, further differentiation was not possible. Therefore, the super-efficient SBM model was employed to distinguish between the

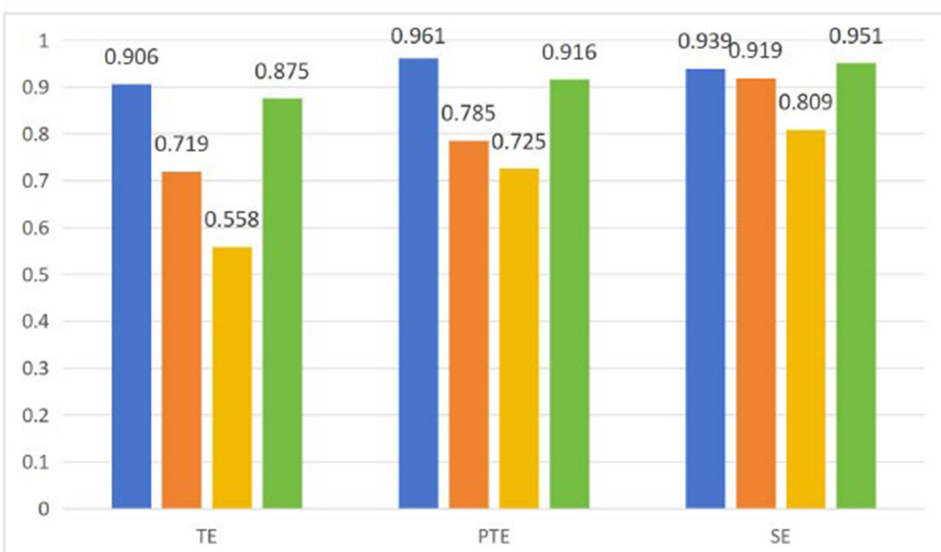

Figure 7 Regional Averages of Provincial Health Productivity in China, 2020. This bar chart illustrates the average health productivity scores across four regions in China for the year 2020. The regions are categorized as Eastern Region (blue), Central Region (Orange), Western Region (yellow), and Northeast Region (green). Three indicators are compared: TE (Technical Efficiency), PTE (Pure Technical Efficiency), and SE (Scale Efficiency). Each bar represents the average score for each region across these indicators, highlighting regional disparities in health productivity.

effective DMUs, which were sorted and analyzed. The study utilized MaxDEA Ultra 8.0 software for measurement, as depicted in Table 5.

The results of the super-efficient SBM model showed that China's provincial health production efficiency in 2020 had a mean value of 1.020 and a median of 0.992. Health production efficiency of 11 provinces was above the mean value. The most efficient province was Guangdong (2.276), and the least efficient province was Qinghai (0.351). It indicates that regional disparities are significant in China's provincial health production efficiency. Though the overall level was relatively high, optimization and improvement are still needed in further.

According to the ranks, the top five provinces except for Jiangxi, locate in the eastern region. It suggests that the eastern region demonstrates a higher level of economic development, medical and health technology, and management standards. Conversely, technical efficiency was less than 1 in all provinces of the western region, except for Guangxi. Inner Mongolia, Xinjiang, and Qinghai occupied the last three positions. It indicates that the western region lagged in terms of development and had lower management standards. Additionally, due to the vast geographical area and low population density in these provinces, the allocation of health resources was more challenging, leading to lower efficiency in health production.

Longitudinal Intertemporal Analysis of Malmquist's Index Model of Productivity Change

Overall Analysis of Changes in Health Productivity in China

This study utilizes panel data from 2010 to 2020 to further analyze the inter-period trends in health service productivity in China at the provincial level. The output-oriented DEA-Malmquist index model is selected for analysis. The study presents the trend of health service productivity change in each inter-period interval and the average of the 10 inter-period intervals in Table 6 and Figure 8.

Table 5 Health Productivity and Ranking of Provinces in China, 2020

ranks	DMU	TE	Ranks	DMU	TE
1	Guangdong	2.276	17	Shaanxi	0.864
2	Jiangxi	2.254	18	Anhui	0.849
3	Tianjin	1.542	19	Guizhou	0.800
4	Hebei	1.534	20	Liaoning	0.755
5	Zhejiang	1.391	21	Yunnan	0.749
6	Shanghai	1.372	22	Sichuan	0.743
7	Guangxi	1.325	23	Ningxia	0.691
8	Jilin	1.301	24	Hainan	0.683
9	Beijing	1.283	25	Shanxi	0.677
10	Jiangsu	1.261	26	Chongqing	0.674
11	Fujian	1.180	27	Hunan	0.608
12	Henan	1.109	28	Hubei	0.581
13	Tibet	1.018	29	Inner Mongolia	0.541
14	Heilongjiang	1.001	30	Xinjiang	0.354
15	Gansu	0.928	31	Qinghai	0.351
16	Shandong	0.922			

Table 6 Malmquist Index of Health Productivity in China, 2010–2020

Time Periods	Technical Efficiency Changes	Pure Technical Efficiency Changes	Scale Efficiency Changes	Total Factor Productivity Change
2010–2011	0.981	0.989	0.992	1.002
2011–2012	1.016	1.056	0.963	0.990
2012–2013	1.025	1.031	0.995	1.020
2013–2014	0.956	1.016	0.941	0.948
2014–2015	1.045	1.038	1.007	1.006
2015–2016	1.011	1.011	1.001	0.995
2016–2017	0.983	1.004	0.979	0.983
2017–2018	0.832	0.818	1.018	1.082
2018–2019	1.257	1.306	0.963	0.950
2019–2020	0.997	0.964	1.034	1.047
Average	1.006	1.017	0.989	1.002

The average value of the DEA-Malmquist index for the 31 provinces in China from 2010 to 2020 was 1.002, indicating an increase in total factor productivity. From 2017 to 2020, there was a noticeable fluctuation in the trend of total factor productivity change, following a pattern of "rising-declining-rising". This trend aligned with changes in scale efficiency, suggesting an overall improvement in China's health production efficiency over the decade, largely driven by scale efficiency.

From a technical efficiency perspective, it was noted that technical efficiency changes in the remaining 9 time periods consistently exceed 0.95 except for 2017–2018. Notably, 4 time periods exhibited a technical efficiency above 1.000, suggesting an overall higher management level within health service organizations, consequently enhancing efficiency.

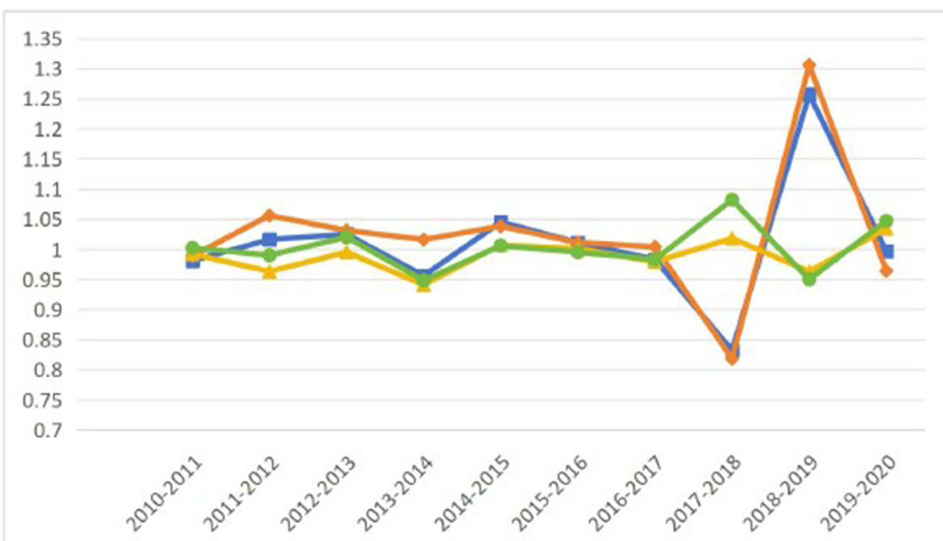

Figure 8 China's Health Productivity Malmquist Index Line Graph, 2010–2020. This line graph illustrates the trends in health productivity across China from 2010 to 2020, as measured by the Malmquist index. The graph features four key indicators: TE (Technical Efficiency, represented in blue), PTE (Pure Technical Efficiency, shown in Orange), SE (Scale Efficiency, indicated in yellow), and TFP (Total Factor Productivity, depicted in green). Each line corresponds to the average index value for each indicator over the specified periods. The data reveals fluctuations and trends in health productivity, with notable peaks and troughs, particularly emphasizing a significant increase in PTE and TFP during the period from 2018 to 2019. This visualization aids in comprehending the dynamics of health productivity improvements throughout the decade.

Before 2017, technical efficiency remained relatively stable over time, indicating a consistent management level within these organizations. After 2017, noticeable fluctuations in changes were observed displaying a "decline-rise-decline" trend in PTCE. This suggests that the current index system evaluation was impacting the existing technical and management levels. In the periods of 2017–2018 and 2019–2020, scale compensation efficiency surpasses 1.000, indicating a state of increasing returns to scale. It implies that scale efficiency positively influences healthy production efficiency, leading to an enhancement in the overall production process. The average value of scale efficiency tends towards 1, suggesting an optimal production scale is being reached, stabilizing the scale efficiency state.

Analysis of Changes in Health Productivity in 31 Provinces of China

The levels of changes in health productivity in China's 31 provinces from 2010 to 2020 were presented in Table 7. The average total factor productivity change index is slightly higher at 1.002 compared to 1.000, suggesting a modest increase in overall health productivity in China. Among the 31 provinces, 18 provinces including Beijing, Tianjin, Hebei, Jiangsu, Zhejiang, Fujian, Guangdong, Shanxi, Henan, Inner Mongolia, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Liaoning, Jilin, and Heilongjiang, showed total factor productivity changes above 1.000, indicating an upward trend in health production efficiency. In terms of scale efficiency changes, 8 provinces such as Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Jiangxi, Hunan, and Jilin have values above 1.000, suggesting that the current indicator system may be limiting the efficiency of health production in these areas. Regarding pure technical efficiency changes, 22 provinces had values equal to or above 1.000, indicating that technological development and improvements in management practices were positively impacting health efficiency.

Table 7 Malmquist Index of Health Productivity in China's Provinces, 2010–2020

Decision Making Units	Technical Efficiency Changes	Technological Changes	Pure Technical Efficiency Changes	Scale Efficiency Changes	Total Factor Productivity Changes
Beijing	1.055	0.988	1.050	1.004	1.042
Tianjin	1.052	0.985	1.043	1.009	1.036
Hebei	1.027	0.985	1.028	0.999	1.011
Shanghai	1.000	0.985	1.000	1.000	0.985
Jiangsu	1.000	1.006	1.000	1.000	1.006
Zhejiang	1.040	0.974	1.036	1.003	1.013
Fujian	1.012	0.992	1.042	0.971	1.004
Shandong	0.983	0.992	0.992	0.991	0.974
Guangdong	1.037	0.978	1.044	0.993	1.015
Hainan	0.986	0.980	1.003	0.983	0.967
Shanxi	1.016	1.015	1.030	0.986	1.032
Anhui	0.976	0.981	0.985	0.992	0.958
Jiangxi	1.000	0.998	1.000	1.000	0.998
Henan	0.993	1.012	1.013	0.980	1.004
Hubei	0.970	1.011	0.970	0.999	0.980
Hunan	0.978	0.994	0.969	1.009	0.972

(*Continued*)

Table 7 (Continued).

Decision Making Units	Technical Efficiency Changes	Technological Changes	Pure Technical Efficiency Changes	Scale Efficiency Changes	Total Factor Productivity Changes
Inner Mongolia	1.004	1.032	1.009	0.995	1.036
Guangxi	1.000	0.970	1.054	0.949	0.971
Chongqing	0.969	1.015	0.974	0.995	0.984
Sichuan	0.988	1.009	0.995	0.993	0.997
Guizhou	0.941	1.003	0.978	0.962	0.944
Yunnan	0.960	0.968	0.978	0.981	0.929
Tibet	0.933	0.984	1.021	0.913	0.918
Shaanxi	1.019	1.026	1.025	0.994	1.046
Gansu	1.050	0.989	1.079	0.974	1.038
Qinghai	0.987	1.030	0.990	0.997	1.016
Ningxia	1.028	0.990	1.036	0.993	1.018
Xinjiang	1.034	1.021	1.035	0.999	1.056
Liaoning	1.023	0.990	1.031	0.992	1.013
Jilin	1.074	0.991	1.073	1.001	1.065
Heilongjiang	1.058	0.984	1.062	0.996	1.041
Average	1.006	0.996	1.017	0.989	1.002

Total factor productivity changes can be broken down into technical efficiency changes and technological changes. By using technical efficiency changes as the horizontal axis and technological changes as the vertical axis, a scatter plot was created for the data of 31 provinces, as depicted in Figure 9. The scatter plot allows for a simple categorization of China's 31 provinces into four groups, as outlined in Table 8. The first category consists of regions where both technical efficiency change and technical change are greater than or equal to 1, indicating an increase in technological progress and innovation in health services, improved management levels of health organizations, and an overall upward trend in efficiency. Conversely, the provinces in the fourth category need to enhance their technological progress and management levels to boost health efficiency. The largest proportion of provinces falls into the second category, where technical efficiency change is greater than or equal to 1 and technical change is less than 1, accounting for 45.16%.

Trends in Health Productivity

Intra-Regional Variations

The Dagum Gini coefficient, as depicted in Figure 10, has exhibited a fluctuating downward trajectory, suggesting a gradual narrowing of disparities in health productivity nationwide. Specifically, the northeast and eastern regions had maintained low Gini coefficients, indicating minimal internal variances between these regions. To further analyze the evolution of the Gini coefficient, it can be segmented into two distinct time frames centered around 2017: (1) From 2010 to 2017, the overall national Gini coefficient displayed a gradual decrease, with the western region experiencing a more pronounced decline and the northeastern region demonstrating sporadic upward fluctuations. (2) Between 2017 and 2020, the overall Gini coefficient increased before decreasing, with the eastern region consistently reducing its Gini coefficient, while the other three regions exhibited more significant fluctuations.

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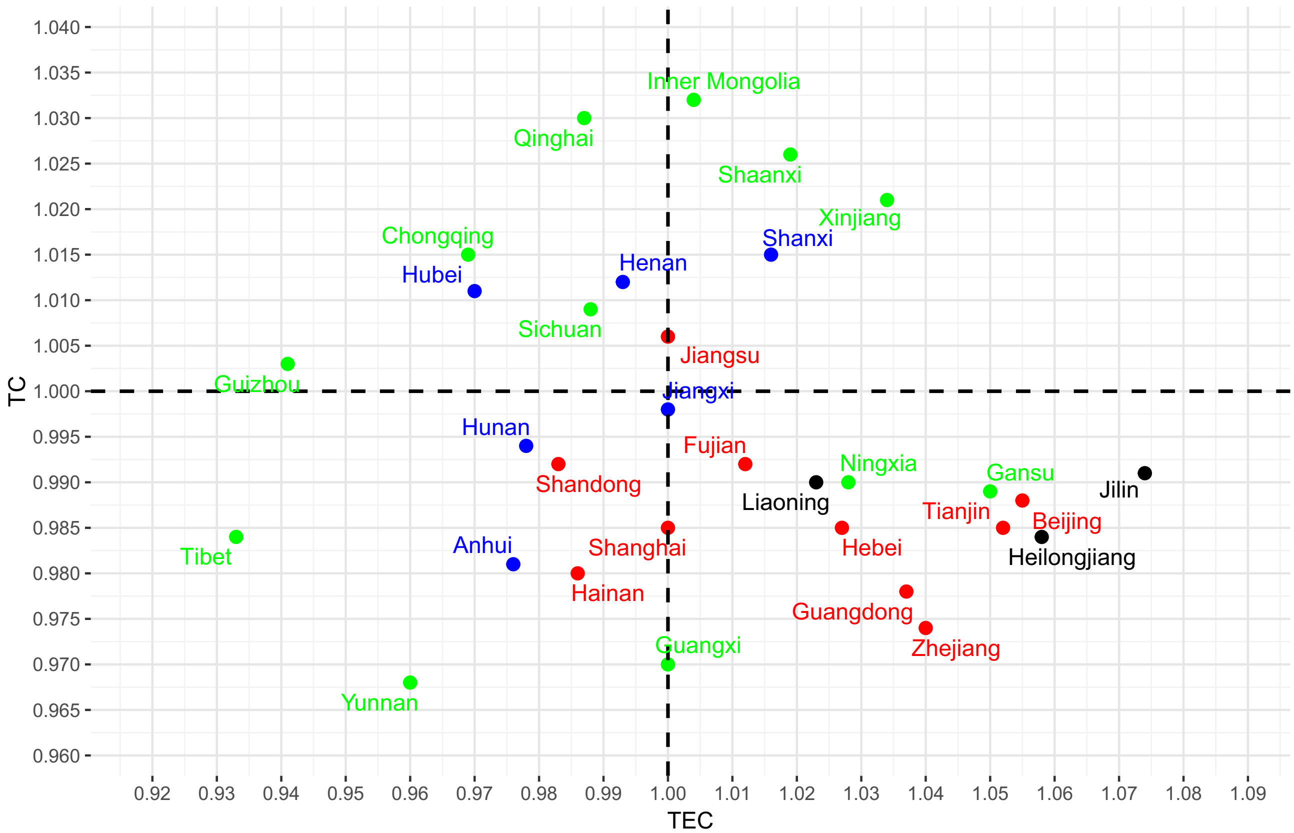

Figure 9 Scatterplot of Malmquist Index Situation in Provincial Administrative Regions of China, 2010–2020. This scatterplot illustrates the Malmquist Index scores for various provincial administrative regions in China over the decade from 2010 to 2020. The Malmquist Index comprises two components: Technical Efficiency Change (TEC) on the x-axis and Technical Change (TC) on the y-axis. Each point on the plot represents a province, color-coded by region: Central region (red), Eastern region (blue), Northeastern region (green), and Western region (black). The dashed line at TEC = 1 and TC = 1 serves as a reference, indicating no change in efficiency or technology. Provinces positioned above this line have experienced improvements in either efficiency or technology, or both, during the specified period. This visualization effectively highlights regional disparities and advancements in health productivity across China.

Inter-Regional Differences

The inter-regional Gini coefficient serves as an indicator of the disparity between China's four major regions. A large value suggests a significant gap, while a small value indicates a smaller gap. Table 9 shows China's health productivity inter-regional differences. Overall, the Gini coefficient between regions shows a general downward trend, signaling a growing focus on inter-regional collaboration among the major regions and a reduction in disparities. However, the disparity in the mean Gini coefficient value between the eastern and western regions remained substantial and consistently high, with an upward trajectory. Therefore, efforts should be directed towards enhancing the health productivity of the western region to narrow the inter-regional disparities.

Table 8 Changes in Technical Efficiency and Categorization of Technical Changes in China's Provincial Administrations, 2010–2020

Malmquist Exponential Decomposition	Provinces	Percentage (%)
techch ≥ 1 and effch ≥ 1	Jiangsu, Inner Mongolia, Shaanxi, Xinjiang, Shanxi	16.13
techch < 1 and effch ≥ 1	Jiangxi, Shanghai, Guangxi, Fujian, Liaoning, Hebei, Ningxia, Gansu, Tianjin, Beijing, Heilongjiang, Jilin, Guangdong, Zhejiang	45.16
techch > 1 and effch ≤ 1	Guizhou, Hubei, Chongqing, Qinghai, Henan, Sichuan	19.35
techch ≤ 1 and effch ≤ 1	Tibet, Yunnan, Anhui, Hainan, Shandong, Hunan	19.35

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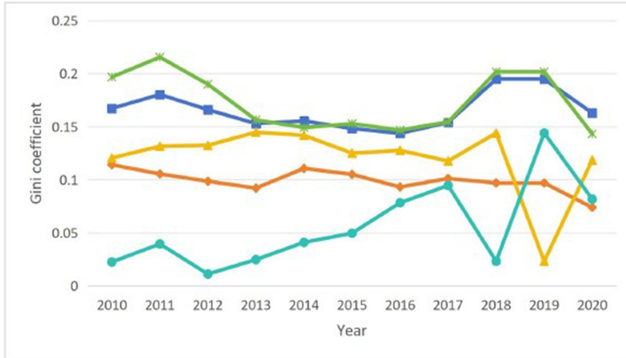

Figure 10 Trends in Health Productivity and Intra-Regional Differences, 2010–2020. This line graph illustrates the Gini coefficients, a measure of income inequality, across different regions from 2010 to 2020. The Gini coefficient ranges from 0 (perfect equality) to 1 (perfect inequality). The graph shows the overall Gini coefficient along with regional data for the Eastern, Central, Western, and Northeast regions. Overall Coefficient (Blue Line with Square Markers): Represents the national average Gini coefficient, indicating the overall income inequality trend across the country. Eastern Region (Orange Line with Diamond Markers): Displays the Gini coefficient for the Eastern region, showing moderate fluctuations over the decade. Central Region (Yellow Line with Triangle Markers): Represents the Gini coefficient for the Central region, with a relatively stable trend but a noticeable dip in 2019. Western Region (Green Line with Star Markers): Illustrates the Gini coefficient for the Western region, which shows a general decreasing trend with a peak in 2011. Northeast Region (Cyan Line with Circle Markers): Represents the Gini coefficient for the Northeast region, which exhibits a significant increase from 2010 to 2017, followed by a sharp decline. The graph highlights the varying trends in income inequality across different regions, with the Western region showing the most significant decrease in inequality, while the Northeast region experienced a notable increase before a sharp decline. The overall trend suggests a slight decrease in national income inequality over the decade.

Summary and Conclusion

This study utilizes the traditional BCC model, the DEA-Malmquist index model, and the super-efficient SBM model in data envelopment analysis to assess the health production efficiency among 31 provinces in China. By employing multidimensional scientific measurements, the study examines inter-period changes and regional relative differences in health production efficiency. The Dagum Gini coefficient and its decomposition method are used to analyze regional disparities. The findings reveal an overall improvement in China's health level with increasing input and output, which lead to significant health outcomes. Regional disparities are same to decrease over time. Though health production efficiency was generally high in China, there are still problems need to be improved such as input redundancy and output slack which primarily influenced by the health input scale. Significant regional differences persist among four major

Table 9 Inter-Regional Differences in Health Productivity

Year	Inter-regional Gini Coefficient					
	East-central	East-west	East-northeast	Central-west	Central-northeastern	West-northeast
2010	0.13191	0.17992	0.18258	0.19064	0.22368	0.17294
2011	0.13348	0.19116	0.22642	0.21334	0.26082	0.19045
2012	0.12188	0.19120	0.22308	0.18683	0.20372	0.16005
2013	0.12473	0.17592	0.18141	0.18648	0.17797	0.13479
2014	0.13326	0.18842	0.17443	0.1786	0.15647	0.12124
2015	0.13354	0.19458	0.13086	0.16034	0.10561	0.11853
2016	0.12029	0.18734	0.11248	0.16706	0.11397	0.13432
2017	0.11944	0.20852	0.12192	0.17829	0.1135	0.15831
2018	0.13225	0.26745	0.24827	0.23841	0.19815	0.14145
2019	0.24827	0.26745	0.13225	0.14145	0.19815	0.23841
2020	0.14589	0.24487	0.08300	0.16591	0.14083	0.22707

regions, with a pronounced gap between eastern and western regions. Targeted measures are recommended to enhance the health productivity of the western region. Based on these findings, recommendations are proposed to address current health production efficiency and existing challenges.

Playing a Leading Role in Government for Scientific and Integrated Planning

Research findings indicate that scale efficiency is a key determinant in enhancing health productivity in China. The government should take the lead in developing health plans tailored to the unique environmental characteristics, health service demands, and overall health status of each region. It should be done while considering the economic and demographic trends of each area and ensuring the effective allocation of health resources. By establishing an efficient and equitable public health service and medical care system, the utilization of health resources can be optimized, leading to improved health outcomes, fairer resource distribution, and ultimately, the successful implementation of the "Healthy China 2030" initiative.

Optimizing the Allocation of Health Care Resources and Developing Standardized Evaluation Criteria

Each region should establish standardized periodic evaluation criteria and adjust inputs based on evaluation results to optimize medical and healthcare resource allocation. Regions with low health productivity should create favorable conditions by implementing preferential policies to attract high-quality medical personnel, expanding medical equipment utilization and strengthening quality management. This proactive approach can help overcome low health productivity bottlenecks and enhance health levels and resource efficiency.

Scientific Measurement of Health Productivity and Exploration of Interregional Synergies

The government should prioritize the disparities in health productivity across different regions, particularly focusing on the variations between the eastern and western regions. It's crucial to establish a connected and unified information management platform by emphasizing the development of digital health and leveraging information technology support. This platform would help break down information barriers between regions and facilitate technological exchanges, enabling the sharing of health advancements. Simultaneously, efforts should be targeted for efficiency imbalances within the same region. By establishing a regional health production efficiency measurement group, the government can regularly assess the health production efficiency of provinces in the region, monitor changes, and conduct scientific evaluations. Tailored support can be provided to regions with both high and low efficiency to enhance overall health productivity in the area.

Optimizing the Central Financial Transfer Policy to Reduce the Disparity Between the Eastern and Western Regions

This study highlights the disparity in health productivity between the eastern and western regions of China, attributing it to factors such as economic development, population density, and financial support. The findings suggest a "depression effect" between the regions. To address this imbalance, it is recommended that policies and financial support should be directed towards the development of healthcare in the western region, such as optimization of central financial transfer payments furtherly favoring the western region. Furthermore, efforts should be made to enhance self-development capacity in the western region by investing in human resources, improving the professional skills of medical personnel, and increasing healthcare productivity through position transfers and counterpart support.

Data Sharing Statement

All data generated or analyzed during this study are included in this published article.

Acknowledgments

This paper has been uploaded to ResearchSquare as a preprint: https://www.researchsquare.com/article/rs-4681198/v1.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Funding

There is no funding to report.

Disclosure

The authors report no conflicts of interest in this work.

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