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EVALUATION AND OPTIMIZATION OF HOSPITAL SYSTEM IN CHINESE PROVINCES: DOES MORTALITY MATTER?

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Abstract. During the production process of goods and services, sometimes undesirable outputs are difficult to avoid. However, this aspect is often ignored. Hospitals produce patient care, but undesirable outputs do arise. The novelty of this paper is to introduce the mortality as an undesirable output into the derivation of the public hospital efficiency measure. Similar to the production of economic goods and pollution where the latter increase along with the former, our description of mortality in hospital is considered as weakly disposable. Based on an extension model of Kuosmanen [*Am. J. Agric. Econ.* **87** (2005) 1077–1082], we evaluate the public hospital efficiency with and without incorporating mortality under four scenarios. We apply this model to measure public hospital efficiency in Chinese provinces. The results indicate that no matter whether one considers undesirable outputs within the objective functions, it has a significant impact on benchmarking once the mortality is included to define the production technology.

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1. Introduction

Over the last 30 years, China's public healthcare system has experienced a number of reforms. The government presented the "Opinions on Deepening the Reform of the Health System", in March 2009, thereby launching the third round of large-scale reform of the hospital system . This round of reforms emphasizes the healthcare equity, mainly focusing on two aspects: improving hospital insurance coverage and strengthening the service capacity of primary hospital institutions [59]. The Chinese government has promised to provide essential hospital services equally to all citizens by 2020 (see [57]). Public hospitals have gradually carried out a series of reforms to improve their performance [38]. The "Sixth National Health Service Statistical Survey Report" shows that the coverage rate of basic hospital insurance in 31 provinces has reached 96.8% [43]. At the same time, the aging population and life expectancy of Chinese society are increasing. According to the seventh census data, the number of persons aged 60 and up has risen to 260 million in China [41]. On January 10, 2022, the "14th Five-Year" Public Service Plan issued by the National Development and Reform Commission and other departments shows

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that China's average life expectancy in 2025 will reach 78.3 years. With the improvement of the coverage rate of the healthcare security system, the demand for public hospital services increased and it is coupled with increasing expenses. This undoubtedly places higher requirements on the quantity and quality of public hospital supplies in China. However, along with the growing demand for healthcare services, medical expenditure continues to increase, hence public hospitals face great pressure on resources under this plan [24, 30, 37, 59].

Before the third round of healthcare system reforms implemented in 2009, the efficiency of public hospitals in China has been considered poor in terms of quality, access, and costs [25]. Further improvement of public hospitals' efficiency can improve the ability to respond to public health emergencies and effectively alleviate the pressure of the people's growing healthcare needs. Governments, hospitals, and researchers in China are focusing on how to efficiently monitor and improve the performance of public hospitals. In the post-pandemic period, China's overall economic growth slowed down, and health resources' growth has been limited [26]. Facing the challenges of an aging population and the pandemic, improving the utilization efficiency of resources devoted to public hospitals is crucial.

To measure the allocation of resources in China's public hospitals we choose public hospitals' input-output data in various provinces from 2011 to 2019. To clarify the effects of including undesirable outputs in the production technology, we develop four different models. By evaluating the performance of public hospitals under four different scenarios, the characteristics and problems of public hospitals in China are revealed. Targeted suggestions and countermeasures are put forward to provide a scientific basis for formulating development plans, coordinating hospital resource allocation, and rational decision-making. Even though the data are pre-pandemic, recommendations can be made regarding the public hospital system in China to respond to future health-related surges in demand as well as to the continuing growth of the elderly population and their increased needs for healthcare.

The remainder of this research is structured as follows. We compile and review significant studies on healthcare efficiency in Section 2. In Section 3, we introduce data and models, including data description and model setting. Section 4 provides results of efficiency performance, including a discussion of differences across scenarios and regions. In Section 5, we present conclusions and give suggestions for policymakers based on empirical results.

2. Literature review: Hospital efficiency and mortality

The research on efficiency has a long history [7, 47]. Past research has been divided into two categories: parametric methods, such as stochastic frontier analysis (SFA), and nonparametric methods, for instance, data envelopment analysis (DEA). Antunes *et al.* [2] propose a new DEA method to analyze a panel dataset covering 39 commercial banks in China from 2010 to 2018 to estimate efficiency. Liddle and Sadorsky [35] apply SFA to evaluate the energy efficiency of 81 OECD and non-OECD countries from 2000 to 2013. Xie *et al.* [56] use SFA approach to calculate the energy efficiency score and potential energy-saving of Chinese provincial transportation sector from 2007 to 2016. Chen *et al.* [9] use a Bayesian SFA model considering heterogeneity to examine the cost efficiency of Chinese hospitals at the provincial level over 2002–2011.

There are some limitations of the SFA method when measuring hospitals' efficiency. First, the predefined production function may not be valid for all decision-making units. Second, SFA relies on a random error term to set the probability distribution, and a single region can easily impact the frontier production function [36]. Also, SFA presupposes a minimum cost function which may incur misspecification especially for hospitals that may not follow the economic norm of cost minimization/profit maximization.

Unlike the SFA approach, using the DEA method, it is not necessary to specify the functional form of the production technology. It is appropriate for boundary production functions with multiple inputs and outputs. Furthermore, the DEA method has no special requirements on the dimension of each index, and inputs and outputs can be measured in their natural units.

Given the reasons mentioned above, DEA is more widely used in computing hospital efficiency [5]. Under the framework of dynamic network DEA, See *et al.* [48] use a non-convex frontier method to evaluate the technical efficiency (TE) of hospital pharmacies between specialty and non-specialty hospital categories. Jahantigh and

Ostovare [28] use an outcome-based DEA model, based on four input factors and eight output factors, to evaluate the effectiveness of Tehran's 40 medical science university hospitals. Sultan and Crispim [53] use an input-oriented DEA model to investigate the TE of 11 public hospitals in Palestine from 2010 to 2015. Flokou *et al.* [23] apply the nonparametric method of DEA to compute the efficiency of the public hospital system in Greece during the 5-year economic crisis (2009–2013). A survey of DEA studies in hospital/healthcare can be found in Nepomuceno *et al.* [46], O'Neill *et al.* [45], Tiemann *et al.* [54], and Kohl *et al.* [31].

Public hospitals are the main healthcare institutions providing patient care services in China and the main target of the government's healthcare system reform [18]. Therefore, studying whether Chinese public hospitals can effectively provide adequate hospital services is crucial. There has also been extensive literature on this issue in the past two decades (*e.g.*, [4, 9]), especially since China's public hospital system has also undergone many reforms. Every reform has impacted China's public hospital system by increasing insurance coverage leading to more demand for hospital services and by an equitable distribution of resources across hospitals affecting supply.

Driven by the successive reforms of the public hospital system, the efficiency of China's public hospitals has also undergone significant periodic changes. To solve the problem of hospital supports for the rural people, China's government proposed the Rural Cooperative Medical System (RCMS) in the 1950s. The rural cooperative hospital system had covered over 90% of the rural population by the mid-1970s [22]. Then, the government amended the basic social and hospital insurance system for city workers in 1998. All local employers and employees must split health insurance premiums under the plan. By 2007, the penetration rate of the scheme had reached about 65% [16]. In 2009, China implemented its third and most recent reform. This reform proposes establishing and improving the hospital security system to equalize essential public health services. Today, China's hospital insurance system has basically achieved full coverage, covering more than 95% of the population (National Bureau of Statistics [40]).

Taking the last healthcare system reform as a cut-off point, the effects of the third round reform in 2009 have been evaluated in many studies. Jiang *et al.* [29] use DEA to determine the efficiency of 1105 hospitals in 31 Chinese provinces. The results show that from 2008 to 2012, the scale of hospital services and the number of services increased suddenly, but the service performance was not very good and even slightly declined. Chen *et al.* [10] use a method based on the additivity index and cumulative directional distance function (DDF) to evaluate the public hospitals' regional efficiency from 2011 to 2018. According to their findings, the total factor productivity (TFP) of public hospitals is growing at an annual average rate of 1.38%; driven primarily by technical efficiency (TE). Nevertheless, regional disparities in public hospital performance are rising. Chen *et al.* [11] use the three-stage DEA method to evaluate the operational efficiency of public hospitals in 31 provinces in China over the period 2011–2018. They find that the public hospitals' average efficiency scores have increased from 0.92 to 0.98. Furthermore, they find the performance of public hospitals mainly depends on the operating conditions, with 11 district hospitals at the efficiency frontier for the entire period. Although there is an increase in average efficiency, regional differences in public hospital performance persist.

While the Chinese economy is generally centralized, there is an imbalance of regional development, resulting in varying degrees of efficiency of Chinese public hospitals across different provinces or regions. This regional difference has also been found in previous studies. Wang *et al.* [55] use a bootstrapped DEA method to assess the productivity and TE changes in Chinese eastern, western and central county-level public hospitals after the 2012 public hospital reform. It is found that the central region's efficiency scores were consistently lower than those in the western and eastern areas. Hu *et al.* [27] study the Chinese hospitals' efficiency index during 2002–2008 by using DEA tools. They find that the performance of hospital efficiency index in different provinces ranged from 0.396 to 1.00. Based on the data from 2004 to 2008, Ng [44] use DEA to study the efficiency changes of hospitals in China. The empirical results show that the overall efficiency of Chinese hospitals improved throughout this period and find that hospitals in the relatively advanced Pearl River Delta region outperform the western regions. Using the DEA method, Zhang *et al.* [58] investigate regional healthcare efficiency based on provincial hospital data in 1982, 1990, and 2000, and find large efficiency discrepancies in eastern, central, and western China.

It has recently been widely recognized that it is critical to integrate environmental aspects into productive efficiency and productivity measurement. Ancev *et al.* [1] provide a review of the literature on environmentally adjusted productivity measurement since the 1990s and critically discuss the several concepts and methods developed and applied in various contexts. They highlight, among others, that the weak disposability assumption is often used to model pollution-generating technologies in a non-parametric way, which means that the evaluated units can decrease the negative externalities by reducing production activity [32]. Another multi-equation approach relying on the costly disposability assumption (known as the by-production model) is also appealing for economists. The by-production model opens the black box of production by modelling the polluting technology as the intersection of an intended-output technology and a residual-generating technology, which can be modeled with explicitly introducing the mass balance condition and costly disposability [14, 15]. Obviously, there are also methods that do not belong to these cited categories. For instance, Arman *et al.* [3] propose a new approach to find the common set of weights in DEA to examine eco-innovation in the presence of undesirable factors. In the healthcare sector, outputs such as the number of deaths can likewise be viewed as negative externalities. To evaluate hospital efficiency more comprehensively, some studies have begun to consider these undesirable outputs. Hu *et al.* [27] adopt the nonparametric method of DEA to deal with the scenario of multiple outputs with undesirable outputs in the healthcare department. Their results suggest that the efficiency of Chinese hospitals is moderate. Clement *et al.* [13] measure hospital efficiency using the DEA method, adding undesirable outputs such as patient mortality based on traditional output indicators. Bilsel and Davutyan [6] use risk-adjusted mortality as an undesirable output when analyzing hospital efficiency in Turkey.

Given the above review of hospital efficiency studies, we contribute to the literature in three aspects: First, by using more recent inputs and outputs data of public hospitals from 2011 to 2019, the hospital system efficiency of each province in China is measured based on the Kuosmanen [32] model, we can expand on earlier studies. Second, we incorporate the undesirable output gauged as the number of deaths into the DEA model to improve the quality of the evaluation. Third, we specify four different models and use these models to investigate whether the results are impacted by the appearance of undesirable outputs.

3. Methodology

3.1. Production technologies

In evaluation, each hospital is an evaluated unit. The optimal production frontier is constructed by linear programming (LP), and the inefficiency of each evaluated unit is measured through a directional distance function (DDF). Chambers *et al.* [8] introduce the DDF, which is frequently used to calculate the distance between the production frontier (or the best practice) and the evaluated decision-making unit (DMU), namely the provincial hospital. The DDF can measure the degree of inefficiency of the inputs and outputs separately or simultaneously from the perspective of the inputs to produce outputs. Note that in this study, we are more concerned about the impact of mortality on the evaluation results after it was introduced into the efficiency analysis model as an undesirable output. Therefore, we use the output orientation, to facilitate the comparison of inefficient performance under four different scenarios.

While most previous studies measuring hospital efficiency only consider desirable outputs such as the number of operations and discharged patients, we deviate from this earlier approach along with some other studies (see above) by incorporating undesirable outputs such as the number of deaths (as a proxy for quality) to represent a more realistic measurement of hospital efficiency. In particular, to the best of our knowledge we are the first to introduce mortality within the Kuosmanen [32] model applied to evaluate hospital efficiency producing jointly good and bad outputs. We next define the methodological steps we use to derive our efficiency measures.

First, we need to define basic symbols and production technology. Given a J-dimensional input vector $\boldsymbol{x} \in \mathbb{R}_{+}^{\boldsymbol{J}}$, a P-dimensional output vector $\boldsymbol{y} \in \mathbb{R}_{+}^{\boldsymbol{P}}$, and a Q-dimensional undesirable output vector $\boldsymbol{z} \in \mathbb{R}_{+}^{\boldsymbol{Q}}$. Considering two different production processes $\boldsymbol{T}_1$ and $\boldsymbol{T}_2$, the former's input $\boldsymbol{x}$ only produces the desirable output $\boldsymbol{y}$, and the latter's input $\boldsymbol{x}$ can produce both the desirable output $\boldsymbol{y}$ and the undesirable output $\boldsymbol{z}$. Then the production technology or possibility set $\boldsymbol{T}_1$ and $\boldsymbol{T}_2$ can be defined as follows:

$$\boldsymbol{T}_1 = \left\{(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}_+^{J+P} | \boldsymbol{x} \text{ can generate } \boldsymbol{y}\right\} \tag{1}$$

$$\boldsymbol{T}_2 = \left\{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) \in \mathbb{R}_+^{J+P+Q} | \boldsymbol{x} \text{ can produce } (\boldsymbol{y}, \boldsymbol{z})\right\}. \tag{2}$$

Equivalently, these technologies can be represented by their input sets defined as follows:

$$L_1(\boldsymbol{y}) = \left\{\boldsymbol{x} \in \mathbb{R}_+^J | (\boldsymbol{x}, \boldsymbol{y}) \in \boldsymbol{T}_1\right\}, \boldsymbol{y} \in \mathbb{R}_+^P \tag{3}$$

$$L_2(\boldsymbol{y}, \boldsymbol{z}) = \left\{\boldsymbol{x} \in \mathbb{R}_+^J | (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) \in \boldsymbol{T}_2\right\}, \boldsymbol{y} \in \mathbb{R}_+^P, \boldsymbol{z} \in \mathbb{R}_+^Q. \tag{4}$$

In addition, the production technology mentioned above also needs to satisfy some basic economic assumptions, and these general axioms are necessary to make the production technology $\boldsymbol{T}$ ($\boldsymbol{T}_1$ and $\boldsymbol{T}_2$) theoretically sound [21]. We denote the axioms ($\boldsymbol{T}$) to include the following:

$$\begin{aligned}
&(\boldsymbol{T}.1) \quad (0,0,0) \in \boldsymbol{T}, \text{ and if } (0, \boldsymbol{y}, \boldsymbol{z}) \in \boldsymbol{T}, \text{ then } \boldsymbol{y} = 0, \boldsymbol{z} = 0.\\
&(\boldsymbol{T}.2) \quad \boldsymbol{T} \text{ is a closed subset of } \mathbb{R}_+^J \times \mathbb{R}_+^P \times \mathbb{R}_+^Q.\\
&(\boldsymbol{T}.3) \quad \text{For each input } \boldsymbol{x} \in \mathbb{R}_+^N, \boldsymbol{T} \text{ is bounded.}\\
&(\boldsymbol{T}.4) \quad \text{If } (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) \in \boldsymbol{T} \text{ and } (\boldsymbol{x}', \boldsymbol{y}', \boldsymbol{z}') \in \mathbb{R}_+^J \times \mathbb{R}_+^P \times \mathbb{R}_+^Q,\\
&\qquad\quad \text{then } (\boldsymbol{x}', -\boldsymbol{y}', \boldsymbol{z}') \geq (\boldsymbol{x}, -\boldsymbol{y}, \boldsymbol{z}) \Rightarrow (\boldsymbol{x}', \boldsymbol{y}', \boldsymbol{z}') \in T.\\
&(\boldsymbol{T}.5) \quad \boldsymbol{T} \text{ is convex.}
\end{aligned} \tag{5}$$

These axioms can be explained as follows. Inaction is possible and there is no free lunch. Technology is closed and bounded. There is strong disposal of inputs and outputs: we can always waste more inputs for given outputs, and we can always produce less for given inputs. Finally, technology is assumed to be convex: this presupposes that technology is time divisible.

Further, to deal with the relationship between hospitals' desirable and undesirable outputs, we need to add the weak disposability hypothesis [49] and the null-jointness hypothesis [20] in $\boldsymbol{T}_2$. The weak disposability hypothesis holds that the desirable outputs and the undesirable outputs must increase or decrease in the same proportion, and the undesirable output cannot be reduced without reducing the desirable output, and the desirable output cannot be increased without increasing the undesirable output. The null-jointness hypothesis means that when the undesirable output is zero, then the desirable output must also be zero. These weak disposability assumptions and null-jointness assumptions are formally defined as follows:

$$\text{If } (\boldsymbol{y}, \boldsymbol{z}) \in \boldsymbol{T}_2 \text{ and } 0 \leq \theta \leq 1, \text{ then } (\theta\boldsymbol{y}, \theta\boldsymbol{z}) \in \boldsymbol{T}_2. \tag{6}$$

$$\text{If } (\boldsymbol{y}, \boldsymbol{z}) \in \boldsymbol{T}_2 \text{ and } \boldsymbol{y} = 0, \text{ then } \boldsymbol{z} = 0. \tag{7}$$

3.2. Efficiency measures

Efficiency measures provide an equivalent representation of production technologies and focus on positioning observations relative to the boundary of the production possibility set. In this contribution, we use the DDF to measure the hospitals' efficiency. Kuosmanen [32] proposes an approach based on the weak disposability assumption while satisfying both variable returns to scale and convexity assumptions. Following Kuosmanen [32], we define an output-oriented DDF for four different scenarios. The scenario variations are listed in Table 1.

Scenario 1 does not consider the undesirable output, that is, the production technology is solely $\boldsymbol{T}_1$. The efficiency is measured considering only the production of desirable outputs. Using the Chambers *et al.* [8] approach, the DDF framework we employ here can be defined as follows:

$$D(x, y; 0, g_y) = \underset{\theta,\lambda}{\text{Max}} \left\{ \theta \in \mathbb{R}_+ : (y + \theta \times g_y) \in T_1 \right.$$

Table 1. Comparison of four scenarios.

Scenario	Production technology	Objective	Model
1	Without mortality	Expanding desirable outputs	(8)
2	With mortality	Expanding desirable outputs	(9)
3	With mortality	Reducing undesirable outputs	(10)
4	With mortality	Expanding desirable outputs and reducing undesirable outputs	(11)

$$\left.\begin{aligned}
&\sum_{k=1}^{K}\lambda_k y_k^p \geq y_{k'}^p + \theta g_y^p, && p=1,\dots,P\\
&\sum_{k=1}^{K}\lambda_k x_k^j \leq x_{k'}^j, && j=1,\dots,J\\
&\sum_{k=1}^{K}\lambda_k = 1\\
&\lambda_k \geq 0, && k=1,\dots,K
\end{aligned}\right\} \tag{8}$$

where θ is the inefficiency value, which represents the potential improvement space of the evaluated unit in the output orientation. The vector $(0, g_y)$ is a nonnegative directional vector of good outputs, usually defined by the outputs corresponding to the DMUs: this yields a proportional interpretation for the DDF. When θ is greater than zero, then we interpret this as the possible increase in the production of outputs holding inputs constant. The activity variables λ_k denote the reference set variables. If λ_k is greater than zero, then it means that the $\mathrm{DMU_k}$ is referenced as the benchmark determining the projection hypersurface for the optimal production plan.

In Scenario 2, we include the undesirable outputs, defined as the production technology $\boldsymbol{T}_2$. In this scenario, we incorporate both desirable and undesirable outputs data into the DDF framework. However, when measuring inefficiency values, we focus only on the potential improvement in the desirable outputs. That is, we look for the maximum potential when a DMU dedicates all resources to expanding the desirable output (without considering reducing the undesirable output). Therefore, the DDF in this scenario can be defined as:

$$D(x,y,z;0,g_y,0) = \operatorname*{Max}_{\theta,\lambda,\sigma}\left\{\theta \in \mathbb{R}_+ : (y+\theta\times g_y)\in T_2\right.$$

$$\begin{aligned}
&\sum_{k=1}^{K}\lambda_k y_k^p \geq y_{k'}^p + \theta g_y^p, && p=1,\dots,P\\
&\sum_{k=1}^{K}(\lambda_k+\sigma_k) x_k^j \leq x_{k'}^j, && j=1,\dots,J\\
&\sum_{k=1}^{K}\lambda_k z_k^q = z_{k'}^q, && q=1,\dots,Q\\
&\sum_{k=1}^{K}(\lambda_k+\sigma_k) = 1
\end{aligned}$$

$$\left.\begin{array}{ll}\lambda_k \geq 0, \sigma_k \geq 0, & k = 1, \ldots, K\end{array}\right\} \tag{9}$$

where θ is the inefficiency value of the desirable outputs. The vector $(0, g_y, 0)$ is a nonnegative directional vector of good outputs. When θ is greater than zero, then the desirable output can be increased by this proportion holding inputs fixed. The activity variables λ_k and σ_k are the reference set variables. If λ_k and σ_k are greater than zero, then it means that the DMU_k is referenced as the benchmark for the optimal production plan.

Scenario 3 is similar to Scenario 2 in that it is also focuses on production technology $\boldsymbol{T}_2$ but now it is considering the undesirable output. The difference is that in Scenario 3, we focus only on the potential for improvement in the undesirable outputs. That is, the maximum potential when a DMU dedicates all resources to reducing the undesirable outputs without considering expanding desirable outputs. Therefore, the DDF in this scenario can be defined as follows:

$$D(x, y, z; 0, 0, g_z) = \operatorname*{Max}_{\varphi, \lambda, \sigma} \left\{ \begin{array}{ll} \varphi \in \mathbb{R}_+ : (z - \varphi \times g_z) \in T_2 & \\ \sum_{k=1}^{K} \lambda_k y_k^p \geq y_{k'}^p, & p = 1, \ldots, P \\ \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^j \leq x_{k'}^j, & j = 1, \ldots, J \\ \sum_{k=1}^{K} \lambda_k z_k^q = z_{k'}^q - \varphi g_z^q, & q = 1, \ldots, Q \\ \sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1 & \\ \lambda_k \geq 0, \sigma_k \geq 0, & k = 1, \ldots, K \end{array} \right\} \tag{10}$$

where φ is the inefficiency value of the undesirable outputs. The vector $(0, 0, g_z)$ is a nonnegative direction vector of bad outputs. When φ is greater than zero, then the undesirable outputs can be decreased by this proportion holding inputs fixed.

Finally, in Scenario 4, when measuring the inefficiency value, we consider the objectives in Scenarios 2 and 3 at same time under the production technology $\boldsymbol{T}_2$. That is, the maximum improvement potential when a DMU uses all resources to expand the desirable outputs and to reduce the undesirable outputs. Therefore, the DDF in this scenario can be defined as:

$$D(x, y, z; 0, g_y, g_z) = \operatorname*{Max}_{\theta, \varphi, \lambda, \sigma} \left\{ \begin{array}{ll} \varphi \in \mathbb{R}_+ : (y + \theta \times g_y, z - \varphi \times g_z) \in T_2 & \\ \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^j \leq x_{k'}^j, & j = 1, \ldots, J \\ \sum_{k=1}^{K} \lambda_k y_k^p \geq y_{k'}^p + \theta g_y^p, & p = 1, \ldots, P \\ \sum_{k=1}^{K} \lambda_k z_k^q = z_{k'}^q - \varphi g_z^q, & q = 1, \ldots, Q \end{array} \right.$$

Table 2. Inputs and outputs: descriptive statistics.

Variable	Obs	Mean	SD	Min	Max
Staff 1 (Physicans)	279	99 869.81	65 701.84	4043	315 311
Staff 2 (Nurses)	279	106 180	72 061.69	1732	356 330
Staff 3 (Pharmacists)	279	13 667.30	8998.97	428	43 374
Staff 4 (Others)	279	40 946.47	25 040.35	3133	107 581
Beds	279	226 683.60	148 158.30	8352	640 147
Surgical operation	279	1 565 033	1 249 240	23 312	8 372 426
Inpatients	279	6 920 406	4 808 206	145 468	20 200 000
Outpatients	279	6 894 355	4 790 242	144 039	20 100 000
Emergency deaths	279	110 708.40	135 460.70	2275.61	761 389.60
Deaths among hospital discharges	279	24 956.45	20 036.45	95.79	90 708.35
Number of deaths in observation room	279	1298.85	1385.70	9.89	9871.75

$$\left.\begin{aligned} &\sum_{k=1}^{K}(\lambda_k + \sigma_k) = 1 \\ &\lambda_k \geq 0, \sigma_k \geq 0, \qquad\qquad k = 1, \ldots, K \end{aligned}\right\} \tag{11}$$

where θ and φ are the inefficiency values of desirable outputs and undesirable outputs, respectively. The vector $(0, g_y, g_z)$ is a nonnegative directional vector of good and bad outputs. When θ and φ are greater than zero, then it is possible to increase the desirable output by θ, while reducing the undesirable output by φ while holding inputs fixed.

4. Data and results

4.1. Data: Descriptive statistics

To evaluate the improvement of efficiency performance of public hospitals in various provinces after the latest round of medical reform, we use input and output data of public hospitals in 31 provinces in China from 2011 to 2019 to compute their efficiency. Each province is a DMU, and each year is a period to analyze the efficiency performance of each province in each year.

Due to the differences in the functions of different types of hospitals, there are certain differences in hospital services, staff and patients, and production technologies among hospitals. Therefore, we focus on using two types of inputs and two types of outputs. The inputs are employees and beds, among which employees include licensed physicians, registered nurses, pharmacists, and other hospital personnel. Outputs are desirable outputs and undesirable outputs. Desirable outputs include the number of surgeries, hospital admissions, and discharges. Undesirable outputs are different types of mortality, including emergency room deaths, hospital discharge deaths, and observation room deaths. All the data comes from China Health Statistical Yearbooks [42], China Statistical Yearbooks [39], and China Traditional Chinese Medicine Statistical Yearbooks [40]. Descriptive statistics for these variables are shown in Table 2 below: this table contains mean, standard deviation (SD), and the minimum, and the maximum of the data for the in total five inputs and six outputs.

4.2. Efficiency results

Taking the average efficiency of public hospitals in 31 provinces from 2011 to 2019 by year, we can obtain the time trend change of the national average level shown in Figure 1. Note that in Scenario 4, we compute both the potential growth of the desirable outputs and the potential reduction of the undesired output, but we report these two inefficiencies separately.

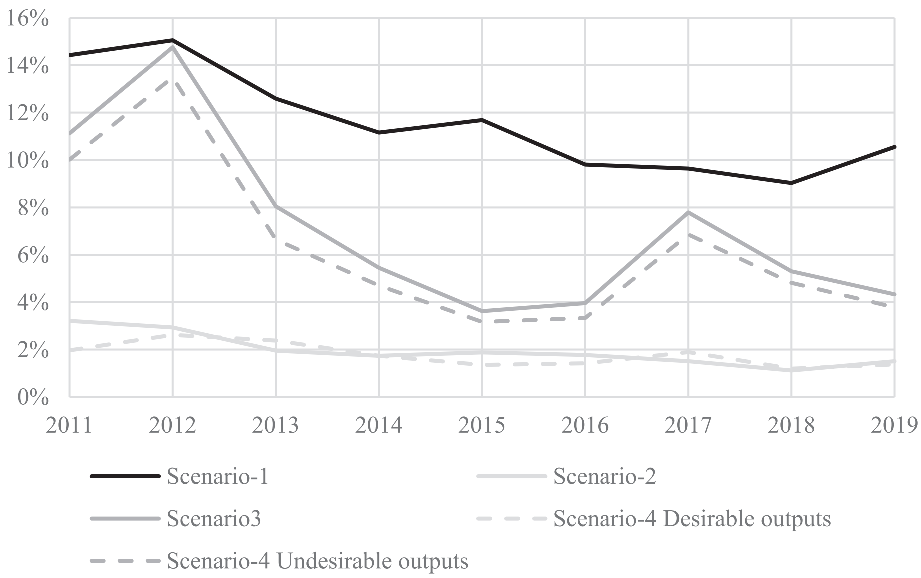


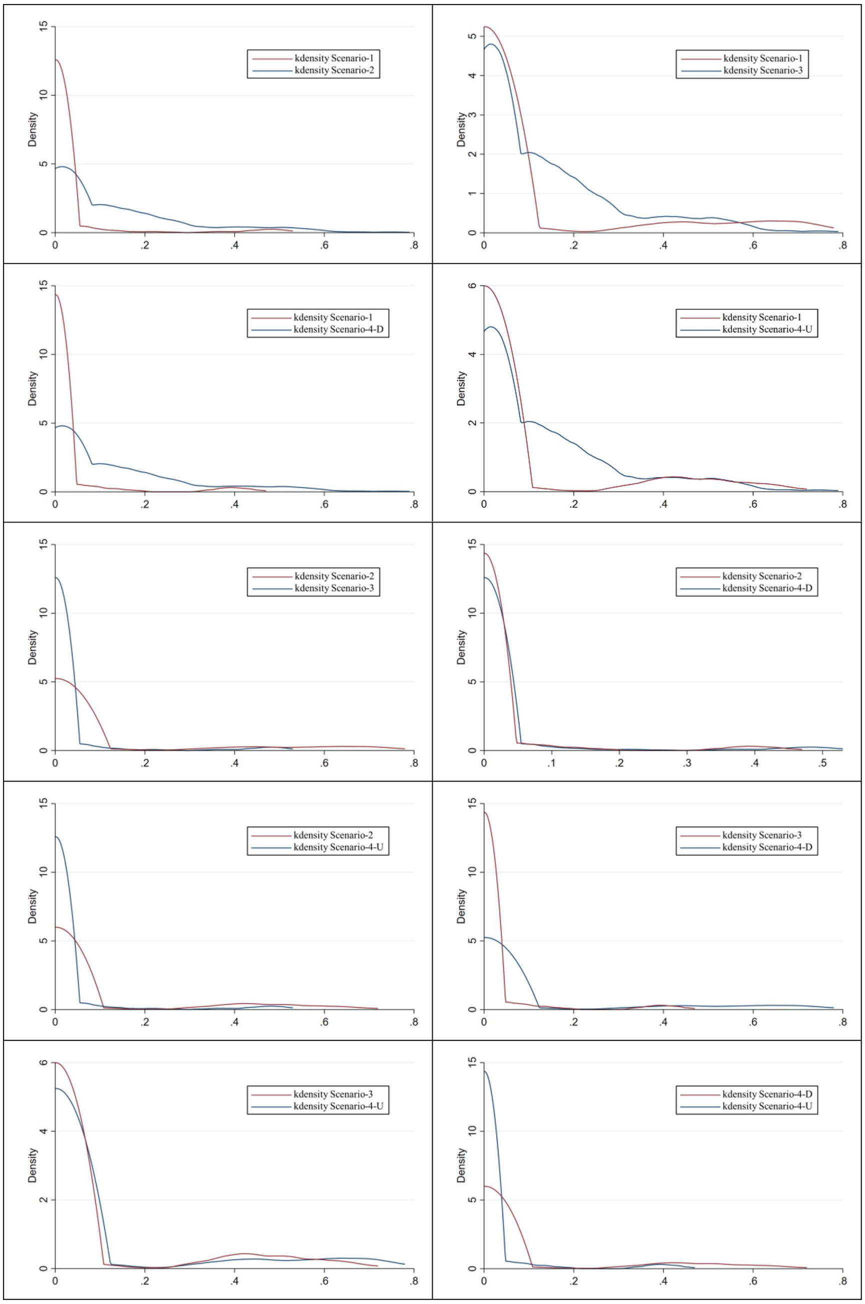
FIGURE 1. Inefficiency level change curve.

As shown in Figure 1, we can find that all inefficiency scores decrease constantly over time. This finding demonstrates that the efficiency performance of Chinese public hospitals is improving. This is in line with the findings of previous studies (see [12, 34]). Specifically, Scenario 1 has a much higher inefficiency value than the other scenarios when undesirable outputs are not taken into account. This may be due to poor technical modeling. The absence of a key indicator (undesirable output) leads to an overestimation of the improvement potential of public hospitals. In Scenarios 2–4, we get results considering the undesirable output. Scenario 2 only measures the inefficiency level of the desirable output, Scenario 3 only measures the inefficiency level of the undesirable output, and Scenario 4 measures the inefficiency level of the desirable and undesirable outputs simultaneously. By comparison, it can be found that the values of inefficiency in Scenarios 2 and 3 is higher than that in Scenario 4, which is reasonable. As resources are limited, when public hospitals use all resources to expand the desirable outputs or reduce the undesirable outputs, their improvement potential is greater than when they improve both at the same time. It is worth noting, however, that the overall improvement potential of public hospitals is greater when both desirable and undesirable outputs are improved.

Comparing the historical inefficiency values of desirable and undesirable outputs we can find that the efficiency of Chinese public hospitals is better in terms of desirable output, with an average inefficiency level of less than 2%. Undesirable output performance is relatively poor, with an average inefficiency level of less than 4%. However, the average inefficiency level of desirable output has not changed much from the time trend, and the degree of improvement is small. The average inefficiency level of the undesirable output has been reduced from the initial 10% to 4%: a relatively significant improvement.

Figure 2 shows the kernel densities of each combination of two models: in total, this figure displays 10 subfigures with two densities. Visual inspection of these density figures shows that the density difference between the models is large in most cases. Li [33] first proposes a non-parametric test to evaluate the differences between densities. The null hypothesis is that both densities are identical. The alternative hypothesis is that both densities differ. Subsequently, Simar and Zelenyuk [52] further modified this algorithm. We use the latter revised method to calculate test statistics and significance levels. The test statistic and the p-value results are shown in Table 3.

The results in Table 3 show that only three groups of models fail the test (Scenario-2 & Scenario-4-D; Scenario-3 & Scenario-4-D; and Scenario-3 & Scenario-4-U), and all the other groups significantly reject the null



Note: Scenario-4-D and Scenario-4-U respectively means the inefficiency of desirable and undesirable outputs.

FIGURE 2. Kernel density estimates of each two models.

Table 3. Statistical values of Li-test.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4-D
Scenario 2	37.265 (0.000)			
Scenario 3	30.223 (0.000)	0.326 (0.022)		
Scenario 4-D	36.474 (0.000)	−0.068 (0.811)	0.281 (0.052)	
Scenario 4-U	30.224 (0.000)	0.331 (0.030)	−0.156 (0.990)	0.284 (0.047)

Notes. The exact p-value is reported in parentheses below.

hypothesis at the 5% significance level. in most cases, the distribution of the two models' results is significantly different. This is also consistent with the results of the kernel density figures.

After removing the 20 efficient provinces or regions, we further compare and analyze the remaining 11 inefficient provinces or regions under the Scenarios 2, 3 and 4 models. The inefficiency levels of desirable and undesirable outputs are shown in Figures 3 and 4 below, respectively.

In Figure 3, only five provinces are not efficient in Scenario 2. While in Scenario 4, the inefficiency levels of these five provinces have decreased. The inefficiency level in Hainan province even dropped to zero. Tibet, Shanxi, Guizhou, and Henan are still inefficient in Scenario 4. It is worth noting that among all the provinces where the desirable output inefficiency level is not zero, Inner Mongolia (Neimenggu) has the highest inefficiency level, reaching 40%. In other provinces, the inefficiency level remains close to 5%. Therefore, the desirable output level of public hospitals in Inner Mongolia has the task for improving efficiency to become more similar to other areas lending evidence that regional differences exist. It is worth noting that, in Figure 4, among all the provinces whose inefficiency level of undesirable output is not zero, Inner Mongolia (Neimenggu) and Liaoning have the worst performance, exceeding 50% and 45% respectively. Except for Henan Province, which has a relatively low level of inefficiency (1%), the other eight provinces have a higher level of inefficiency.

4.3. Regional difference analysis

Furthermore, we divide the 31 provinces into eastern, central and western regions as shown in Table A.1 in the appendix. Then, we get the two average levels of inefficiency in Scenario 4 for public hospitals by region. The comparison of these values with the national average is displayed in Figure 5.

Obviously, both the eastern and western areas have lower levels of inefficiency for both desirable and undesirable outputs than the national average. The central region far exceeds the national average and has the highest degree of inefficiency and the worst performance of hospital efficiency among the three regions. This conclusion is consistent with previous studies (see [27, 44, 55, 58]).

Similarly, we examine the distribution of inefficiencies in different regions. Figure 6 shows the kernel densities of inefficiencies of desirable and undesirable outputs in three regions. This figure displays two subfigures with three densities. The distribution of inefficiencies is basically different in different regions. Also, we do the revised Li-test. The Li-test statistic and the p-value results are shown in Table 4. The results in Table 4 show that only the group (east and west) fail the test in both scenarios, and all the other groups significantly reject the null hypothesis of identical distributions at the 5% significance level.

5. Conclusions, policy recommendations and limitations

As public hospitals are the primary source of healthcare services for the Chinese people, it is critical to investigate their effectiveness in order to improve social welfare. Based on the input and output statistics of 31

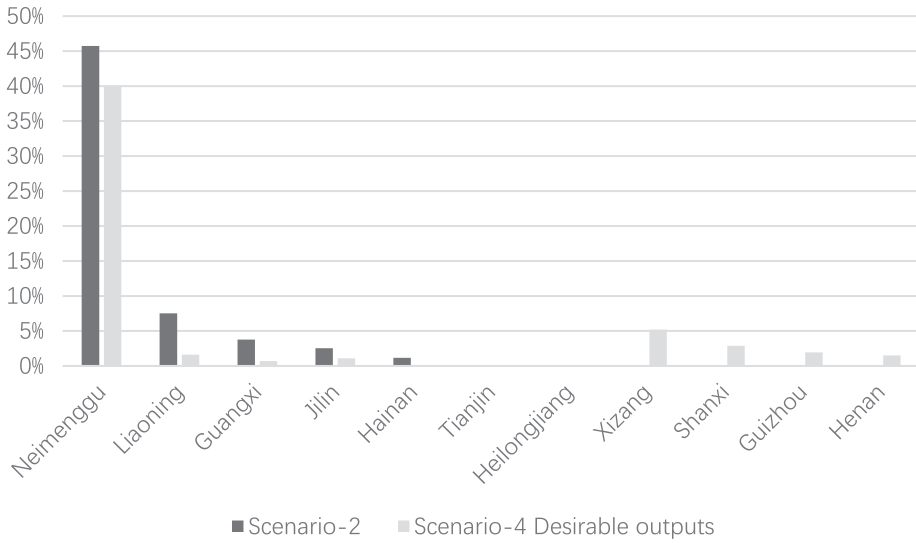


FIGURE 3. Inefficiency level of desirable output.

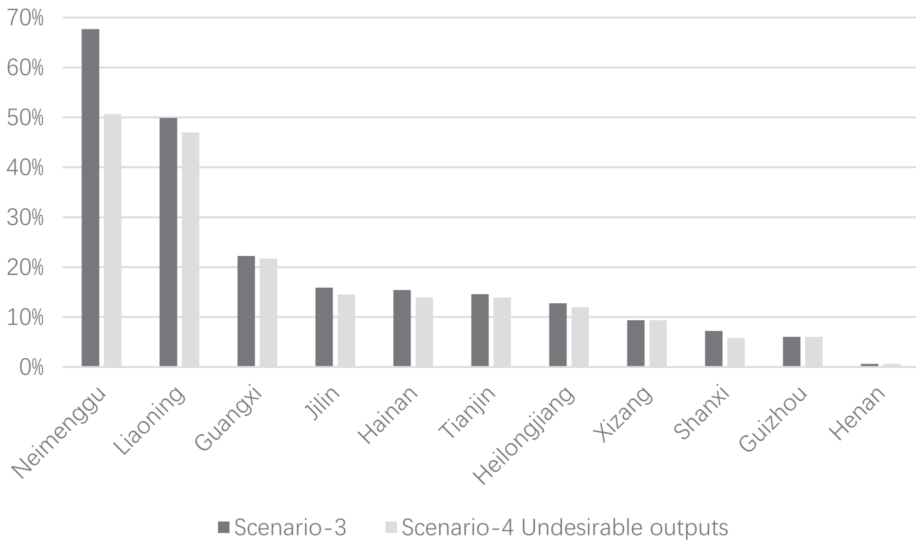


FIGURE 4. Inefficiency level of undesirable output.

Chinese provinces from 2011 to 2019, we measure the changes in the efficiency of public hospitals. To verify the importance of undesirable output in measuring the efficiency of public hospitals, we set four different scenarios and compare the inefficiency values in each scenario. The main conclusions contained in the results are as follows:

First, the average efficiency level of the Chinese public hospital system has been improving over the past nine years. Second, the inefficiency values for each province show that after accounting for undesirable outputs, more than half of the provinces perform optimally. In terms of the production of the desirable outputs, Inner Mongolia's performance is poor. In terms of the production of the undesirable output, Inner Mongolia and Liaoning's performance are rather poor. We interpret these results that public hospitals operating in Inner

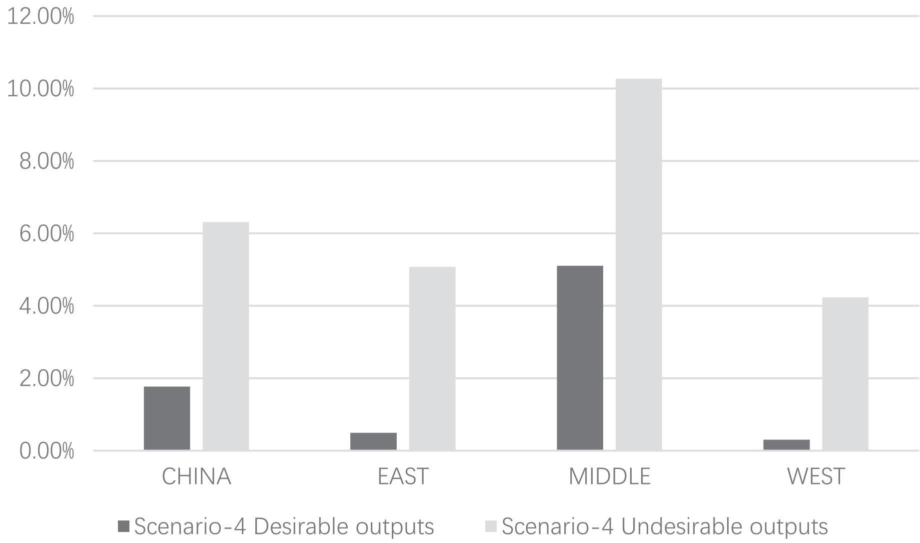


FIGURE 5. Inefficiency level of different regions.

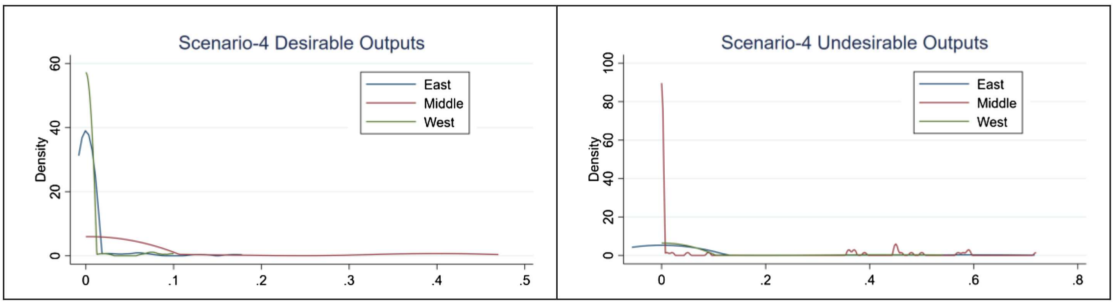


FIGURE 6. Kernel density estimates of inefficiencies in different regions.

Mongolia need to improve both efficiency and quality (as measured by a decrease in mortality rates). Liaoning's public hospitals should focus on improving quality in order to optimize performance. Finally, we compare the average inefficiency levels across regions and found that the inefficiency level in the central region is much higher than in the eastern and western regions.

As we have shown, evaluating hospitals under the four scenarios allows for a more thorough examination of the public hospital system involvement in advancing hospital equalization and optimizing overall hospital efficiency in China. As a result of our findings, the following policy recommendations are made.

First, allocate resources reasonably and control the scale of hospitals. From our findings, it can be found that public hospitals in various provinces differ not only in size, but also in efficiency performance. Regional differences are obvious. Faced with this situation, the government, as the policy-maker in the development of public hospitals, should consider its leading role, allocate resources rationally, and promote the equitable development of public hospitals. When allocating resources, it is necessary to consider the differences geographical and hospital size differences as much as possible. For large hospitals facing diminishing returns to scale expansion should be reduced, and reallocation of redundant human and material resources to avoid wasting resources. For hospitals that are too small, more resources can be appropriately invested to expand their scale of operation

Table 4. Statistical values of Li-test in regions.

Desirable	EAST	MIDDLE
MIDDLE	0.573 (0.007)	
WEST	−0.039 (0.733)	0.608 (0.006)

Undesirable	EAST	MIDDLE
MIDDLE	1.061 (0.002)	
WEST	−0.064 (0.702)	0.721 (0.008)

and improve their service capabilities. It can also promote the reorganization or merger among various hospital institutions and promote the sharing of high-quality resources while reducing operating costs.

Second, enhance the hospital assessment management *via* the introduction of an accountability mechanism for asset performance management. Production processes, including the production of undesirable outputs, have costs. The increase in mortality does not only reduce hospital efficiency, but also means a waste of resources. This type of production without regard to consequences is not conducive to sustainable development. One policy suggestion would be to impose constraints on public hospitals with inadequate asset operation efficiency management. By clarifying the operational positioning of various public hospitals, establishing scale standards for hospitals at all levels, and rationally calculating the input and output between hospitals of different levels, affiliations, and types, the problem can be steadily solved. It can also avoid the waste and inefficiency caused by the misuse of resources. External evaluation methods such as third-party evaluation can be introduced if necessary.

Third, improve the level of technology, promote technological innovation, and enhance the diagnosis and treatment capacity of complex severe diseases. Improve efficiency performance by reducing mortality. Public hospital can strengthen information management, scientifically manage the use and replacement of new and old equipment, appropriately introduce new technologies and new equipment, and improve the awareness of technological innovation. The clinical pathway implementation process and effect evaluation can also be carried out regularly. The quality monitoring of critical links can be strengthened, and the pathway implementation plan can be continuously improved. For province-level hospitals with low efficiency, technological progress can be promoted through hospital alliances and urban-rural integration and other ways to promote the transfer of high-quality hospital resources to inefficient hospitals. At the same time, hospital managers should also actively encourage hospital staff to innovate diagnosis and treatment techniques and processes. This can be accomplished with more precise data collection regarding the cause of patient mortality. With greater precision, hospital managers and other stakeholders can ascertain hospital related quality and not attribute all mortality to hospital quality, especially if patients who do die were beyond medical intervention.

Under all these recommendations, proposals presented are geared toward meeting the dual objective of increasing the desirable outputs of patient care while decreasing the undesirable outputs of in-hospital mortality. By meeting these two objectives, the goals of Chinese hospital reform can be better met. Given the experience of the pandemic, it is necessary that governments and hospitals respond accordingly, including maximizing efficiency without an increase in undesirable outputs. The policy recommendations outlined above can further this endeavor to ensure appropriate inputs to meet future health care crises.

Furthermore, focusing on the time interdependence of production decisions and the adjustment path of the decision-making units over time can be an essential orientation for the future research. Variable factors differ in nature from fixed factors. Identifying the types of inputs can suggest more comprehensive remedies to address inefficiencies (see, *e.g.*, [51]). Dynamic DEA can measure the overall, technical and allocative efficiency of a multi-period production technology [17, 19, 50]. This is a suitable challenge for future research.

Appendix A.

Table A.1. Regions of each province.

Region	Provinces
Eastern	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan;
Central	Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan;
Western	Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

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