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Efficiency Evaluation and Influencing Factor Analysis of China’s Public Cultural Services Based on a Super-Efficiency Slacks-Based Measure Model

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Abstract: It has been established that culture can contribute to the sustainable development of a country and the world. In China, cultural demands are increasing while cultural resources are relatively scarce. Therefore, this paper evaluates the efficiency of public cultural services in China from 2013 to 2017 and analyzes the major factors affecting this efficiency based on the panel data of 31 provinces, municipalities, and autonomous regions (hereafter referred to as “provinces”) in mainland China. The super-efficiency slacks-based measure (SBM) model in Data Envelopment Analysis (DEA) was adopted. The results show that the efficiency of the public cultural services in each province is significantly different, and the overall efficiency shows a downward trend from 2013 to 2017. The gross domestic product per capita, the education level of the residents, fiscal decentralization, and population density significantly impact public culture service efficiency. Based on these results, the following policy recommendations are proposed: (1) Optimize the input structure of public cultural services and adjust the service direction to satisfy the emerging needs for a more diversified and personalized public with economic development and the improvement of education level; (2) adjust the allocation of public cultural resources nationwide and facilitate the flow of public cultural resources from developed to underdeveloped areas; and (3) provide local governments with higher fiscal autonomy and appropriately introduce the Public-Private Partnership (PPP) model to utilize private capital.

Keywords: data envelopment analysis (DEA); super-efficiency SBM; public cultural service efficiency; panel data model

1. Introduction

Culture is the lifeblood of a nation; it gives the people a sense of belonging and is also a powerful driving force for economic and social development. In the Sustainable Development Goals (SDGs) adopted by the United Nations in 2015, culture was mentioned for the first time on the international development agenda. For example, Target 4.7 calls for the appreciation of cultural diversity and culture’s contribution to sustainable development [1]. UNESCO hailed this as an “unprecedented attention” to culture. Hosagrahar pointed out that culture can directly contribute to the sustainable development of economy, society, and the environment and is one of the core objectives of sustainable development [2].

With its rapid economic development, China has become the second largest economy in the world, but the development of China’s public cultural undertakings is lagging behind. For a long period of time, Chinese public cultural investment only accounted for 0.3–0.4% of public fiscal expenditures, which is lower than the average level of 1% in developed countries [3]. Although investments have
increased in recent years, China’s share of fiscal expenditures has continued to decline [4]. The turning point occurred in 2016. After 2016, China began to increase its public cultural input. The total amount of cultural undertakings in 2016–2017 and the proportion of total national fiscal expenditures reached a record high [5], and on 1 March, 2017, “The Law on the Protection of Public Cultural Services” was implemented, the fourth article of which clearly states that the government should “strengthen the construction of public cultural facilities, improve the public cultural service system, and enhance the efficiency of public cultural services.”

In the past, China’s public cultural service sector has long suffered from low service efficiency [6]. “The Law on the Protection of Public Cultural Services” clearly expressed concern about efficiency, which triggered people’s discussion on the efficiency of cultural services. Due to the wide range of public cultural services and the diversity of different cultural service objectives, it is difficult to determine a clear and unified indicator to measure their efficiency. The data envelopment analysis (DEA) method, as an analysis tool for organizational efficiency with multiple input and output indices, has obvious advantages here. This method can be used to evaluate the efficiency of non-profit and public institutions, such as hospitals [7–9], schools [10,11], and courts [12,13] and can also be used for banks [14], cultural industries [15], etc., as well as the evaluation of energy efficiency [16]. Based on these factors, this paper conducts research from two perspectives: (1) using the super-efficiency SBM model in a DEA analysis to evaluate the efficiency of public cultural services in China from 2013 to 2017; (2) discussing and analyzing the main factors that affect the efficiency of public cultural services with the help of panel data models and then putting forward relevant policy recommendations based on the above analyses.

The rest of this paper is structured as follows: Section 2 reviews the literature related to the efficiency evaluation of public cultural services; Section 3 introduces the research methods, index design, and data sources; Section 4 features the analysis of the evaluation results of public cultural service efficiency based on super-efficiency SBM; Section 5 includes a discussion of the factors affecting the efficiency of China’s public cultural services with the help of the panel data model; and the last section provides conclusions and policy recommendations.

2. Literature Review

Different countries have different public cultural service supply models. At present, most models are government-led models represented by France, Japan, and China; market-distributed supply models represented by the United States and Canada; and “Arm’s Length Principle” supply modes represented by the United Kingdom. Through a literature analysis, we found that the current research on the efficiency of public cultural services mainly focuses on the following two aspects.

One is the evaluation and analysis of the efficiency of a certain type of public cultural service, such as public libraries, museums, art galleries, cultural relics, etc. Past studies found that the service efficiency of these public cultural institutions is generally low. For example, Guajardo [17] evaluated the technical efficiency output of 339 non-profit public libraries in the United States using an output-oriented nondiscretionary DEA model with variable returns to scale and found that the nonprofit public libraries in the United States were moderately inefficient in achieving their program and service outputs. Guccio et al. [18] used a network two-stage DEA method to evaluate the protection and use efficiency of ancient books in public state libraries in Italy and found that these libraries had better performance in the protection of ancient books, but their score in the use of ancient books was low. del Barrio et al. [19] used the DEA method to evaluate the efficiency of museums in Spain and found that at least half of the museums operated efficiently, with the primary cause for inefficiency being inadequate resource management, while the impact of technological changes was minor. Basso et al. [20] proposed a new two-stage efficiency evaluation method, the DEA-BSC method, and applied it to the efficiency evaluation of the Venice Municipal Museum. Other scholars found through research that private cultural institutions are more efficient than public cultural institutions. Bertacchini et al. [21] used the count data model to conduct an empirical study on the impact of
ownership and organizational structures on the performance of cultural institutions. They found that the performance of private museums, public museums with financial autonomy, and outsourcing museums was better than that of public museums. Plaček et al. [22] used the DEA method to evaluate the efficiency of museums, art galleries, and monuments in the Czech Republic and found that the efficiency of different institutions varied greatly and could be further improved.

The second aspect is that some scholars use the Data Envelopment Analysis (DEA) model to evaluate the efficiency of China’s public cultural services. Such studies can be divided into two categories based on their input indices: (1) a single index of the financial input and (2) multiple input indices.

Wang et al. [23] analyzed the input and output data of the public cultures of 31 provinces in China from 2003 to 2013. They combined the DEA-Tobit and Malmquist index analyses for the static and dynamic assessment of public cultural expenditures efficiency of local government. Based on the provincial panel data from 2000 to 2015, Tu et al. [24] studied the efficiency of the local government’s public cultural service expenditures and its influencing factors using a two-stage DEA-Tobit methodology. Based on the panel data of 31 provinces from 2000 to 2010, Yang et al. [25] used the super-efficiency DEA and two-step Tobit to compare the fiscal expenditure efficiency of local public cultural services. Based on the provincial panel data from 2013 to 2016, Han et al. [26] used the radial DEA model of super-efficiency to calculate the fiscal expenditure efficiency of public cultural services in different provinces of China. The common conclusion drawn from the highlighted research is that there is a significant gap in the efficiency of public cultural service expenditures in different provinces of China. The efficiency of most provinces should be further improved. At present, there is no obvious cluster effect.

Some researchers have built evaluation systems with multiple input and output indices for the efficiency of public cultural services. The DEA method was used to evaluate the efficiency of public cultural services in each province of China. Based on the data of provincial governments from 2001 to 2013, Shen et al. [27] used a traditional DEA model to investigate the supply efficiency of public cultural services and conducted a principal component regression analysis. The authors found that there were significant gaps in the efficiency of the public cultural services in different provinces. The scale of the government, the proportion of cultural expenditures in fiscal expenditures, and fiscal decentralization have a significant influence on the efficiency of public cultural services, while the level of economic development only has a minor influence. Jiang et al. [28] measured the efficiency of public culture through a DEA-Malmquist model and analyzed the influencing factors of efficiency via a Tobit model based on the provincial panel data of public cultural services in China from 2011 to 2016. They found that both the technical efficiency and total factor productivity of public cultural services in China were decreasing from the east to the west. Moreover, the government’s financial support, professional and technical personnel, cultural market, and urbanization levels are positively correlated to the efficiency of public cultural services. Based on the panel data of 31 provinces from 2012 to 2013, He et al. [29] studied the efficiency of China’s public cultural services using a generalized additive fuzzy DEA model and found that regional public cultural service efficiency has a sparse spatial distribution, and the development of public culture clusters has not been realized.

Thus, the current research on the efficiency of public cultural services is relatively plentiful. Existing studies on the efficiency of China’s public cultural services have large differences in the design of their input and output indices and the factors that affect the efficiency of public cultural services; most previous studies used the traditional DEA or radial super-efficiency model to evaluate the efficiency of public cultural services. In this paper, we adopted the non-radial SBM model of super-efficiency as the research tool. This model can solve the problems of traditional DEA methods, which cannot rank multiple effective decision-making units (DMUs). This model allows the input and output of public cultural services to vary in different proportions and evaluates the efficiency of public cultural services more effectively to determine the corresponding influencing factors. In addition, this paper improved the selection of the input and output indices of public cultural services: The input
indices were designed from the perspectives of human, financial, and material resources, and the output indices were designed mainly from the perspective of public cultural service efficiency. This way, the applied model can better reflect the characteristics of public cultural services and provide a supplement to existing research.

3. Research Methods, Index Design, and Data Sources

3.1. Research Methods

This paper used the slacks-based measure (SBM) model of super-efficiency in its DEA analysis to examine the efficiency of public cultural services in different regions and used the panel data regression analysis model to quantify the main factors affecting their efficiency.

The DEA model is a non-parametric efficiency evaluation method based on the concept of the production frontier and has obvious advantages when dealing with multiple input and output indices. However, in many cases, traditional DEA models (such as CCR models) have multiple valid DMUs (an efficiency value of 1) at the same time. Therefore, it is not possible to directly compare the efficiency of these valid DMUs, which need to be further ranked. Tone [30] proposed using the SBM model of super-efficiency to further rank the efficiency values of DMUs.

The SBM model differs from the traditional CCR or BCC model in that the relaxation variables are directly added to the objective function. Considering \( n \) DMUs and \( m \) inputs per DMU, the inputs are expressed as \( x_{ij} \). There are \( r \) outputs (all expected) expressed as \( y_{pj} \). Assuming that all inputs and outputs are positive, the SBM model evaluates the efficiency of the \( k \)th DMU (\( \rho_k^* \)) using the equation below:

\[
\rho_k^* = \min \rho_k = \frac{1 - \left( \frac{1}{m} \sum_{i=1}^{m} \frac{S^-_i}{x_k} \right)}{1 + \left( \frac{1}{r} \sum_{p=1}^{r} \frac{S^+_p}{y_{pk}} \right)}
\]

\[\text{s.t. } x_{ik} = \sum_{j=1}^{n} x_{ij} \lambda_j + S^-_i, i = 1, \ldots, m \]

\[y_{pk} = \sum_{j=1}^{n} y_{pj} \lambda_j - S^+_p, p = 1, \ldots, r \]

\[\lambda_j \geq 0, j = 1, \ldots, n \]

\[S^-_i \geq 0, i = 1, \ldots, m \]

\[S^+_p \geq 0, p = 1, \ldots, r \]

If and only if \( \rho_k^* = 1 \) (i.e., the slack variables of \( S^-_i, S^+_p \) are both 0), the DMU\(_k\) is an effective unit. If there are multiple effective units, the SBM model of super-efficiency is used to further evaluate these effective units. Assuming that DMU\(_o\) is an effective unit, its unit efficiency is represented by \( \phi_o^* \) in the SBM model of super-efficiency:

\[
\phi_o^* = \min \phi_0 = \frac{1}{m} \sum_{i=1}^{m} \frac{\bar{x}_{io}}{x_{io}} \]

\[\text{s.t. } \bar{x}_{io} \geq \sum_{j=1,j \neq o}^{n} \lambda_j x_{ij}, i = 1, \ldots, m \]

\[\bar{y}_{po} = \sum_{j=1,j \neq o}^{n} \lambda_j y_{pj}, p = 1, \ldots, r \]

\[\bar{x}_{io} \geq x_{io}, i = 1, \ldots, m \]

\[\bar{y}_{po} \leq y_{po}, p = 1, \ldots, r \]

\[\lambda_j y_{po} \geq 0, j = 1, \ldots, n, j \neq o, p = 1, \ldots, r \]
At this point, the efficiency value $\eta_o^* \geq 1$. Higher values indicate that DMU$_o$ is more efficient. Among them, the introduced variables of $\overline{\eta}_{io}$, $\overline{\eta}_{io}$ can be considered an effective combination of the input and output of the other units besides DMU$_o$.

When using the DEA to evaluate efficiency, we need to consider several principles besides the required positive values of the input and output indices. First, a suggested “rule of thumb” is that, to achieve a reasonable level of discrimination, the number of decision-making units should be at least two times that of the product of the numbers of inputs and outputs [31]. Secondly, the input indices should be independent of each other, and the output indices should also be independent of each other. With stronger index independence, the evaluation results will be more accurate [32]. Thirdly, there must be a correlation between the input and output indices (the expected output requires a positive correlation between the input and output indices), otherwise the selected indices are meaningless.

Based on the above principles, this paper preprocessed the original input and output indices. Firstly, principal component analysis was used to reduce the dimensions of the input and output indices. The number of indices was reduced, and the correlation between the indices was eliminated. Then, a positive transformation of the data was carried out. Finally, irrelevant components were removed by a correlation analysis.

After data preprocessing, the principal components were used as input and output indices, and the SBM model of super-efficiency was used to analyze and calculate the efficiency of different provinces. The panel data analysis method was used to explore the main factors affecting the efficiency of public cultural services.

### 3.2. Index Design and Data Sources

According to the China Statistics Yearbook of Culture and Cultural Relics, this paper defines the research object as the cultural services provided by the five major categories of cultural institutions: public libraries, museums, mass cultural institutions (including mass art centers, cultural centers, cultural stations), art performance places, and art performance troupes. The input indices were considered from the three perspectives of human, financial, and material resources. Human resources refer to the total number of employees in cultural institutions, financial resources refer to the investment in cultural undertakings, and material resources refer to the quantities and resources of the five major categories of cultural institutions. The output indices include the utilization of cultural institutions and their resources, cultural services or activities, and the people who benefit from such services. The index system is shown in Table 1.

Based on the China Statistical Yearbook of Culture and Cultural Relics (2014–2018) and the China Statistical Yearbook (2014–2018), the data for the public culture service indicators of 31 provinces in mainland China from 2013 to 2017 were sorted and obtained. The index of cultural undertaking expenditures was converted into a constant price index with 2013 as the base period to eliminate the influence of price changes. The rest were original data.
Table 1. Evaluation index system of public cultural service efficiency in the 31 provinces of China.

| Input Index                                      | Output Index                                      |
|-------------------------------------------------|--------------------------------------------------|
| employees of major cultural institutions        | total amount of circulation (person-times) in public libraries |
| cultural expenditures                           | number of books and periodicals lent by public libraries to readers (copy-times) |
| number of public libraries                      | number of visitors to museums (person-times)     |
| total collections of public libraries           | number of cultural services by cultural institutions |
| number of museums                               | number of people benefiting from the cultural services by cultural institutions (person-times) |
| total collections of museums                    | number of performances at art performance places |
| number of mass cultural institutions            | number of audiences of art performance places (person-times) |
| number of art performance places                | number of performances by art performance troupes |
| number of art performance troupes               | number of audiences of art performance troupes (person-times) |

Notes: (1) Mass cultural institutions: mass art centers, cultural centers and cultural stations specialized in mass cultural activities. Among them, mass art center refers to the mass cultural and art institutions at the provincial, prefecture, and municipal levels established by the state; cultural center is a mass cultural institution at the county and city levels; and cultural station is established by the state and organized by the government, the most basic level of public cultural institutions at the level of townships, towns, urban communities, street offices, district offices. (2) Art performance places: A cultural activity area hosted by the cultural department, which features an auditorium, stage, lighting equipment, and public ticket sales, and is dedicated to the performance of cultural groups. (3) Art performance troupes: All kinds of professional art performance groups sponsored by the cultural department or implemented industry management (examined and approved by the cultural administrative department and with a business performance license), specializing in performing arts and other activities.

3.3. Data Preprocessing

Firstly, the principal component analysis of 9 input indices and 9 output indices was carried out. According to the Bartlett’s test, the KMO values of the input and output indices were 0.746 and 0.745, respectively. The sig. values were 0.000 < 0.05. Therefore, the indices were suitable for the principal component analysis. According to the criterion that the eigenvalue should be greater than 1, three principal input components and three principal output components were extracted respectively, which explained the variances of the original indices (84.326% and 87.747%). After orthogonal rotation, the outcome was the score coefficient matrix, and the principal component score was then calculated.

As DEA requires positive input and output data, the positive transformation of the principal component scores of the input and output was carried out according to Equation (3).

\[
S_i^* = 0.1 + 0.9 \cdot \frac{S_i - min_i}{max_i - min_i}
\]

where, \(S_i\) represents the score of the \(i^{th}\) principal component, and \(S_i^*\) represents the score after positive transformation. \(max_i\) and \(min_i\) represent the maximum and minimum scores of the principal components, respectively, and 0.1 and 0.9 are weights, so \(S_i^* \in [0.1, 1]\). The positive transformation is a linear process, and the weights do not affect the evaluation results.

To meet the correlation requirements between the input and output indices, a correlation test was carried out on the input and output scores. The test results are shown in Table 2. The absolute values of the correlation coefficients between input 3 and 3 outputs were less than 0.2, and the significance level was higher than 0.01. This indicates a weak correlation between input 3 and the outputs; thus, input 3 was removed. Consequently, the model had two inputs \((x_1, x_2)\) and three outputs \((y_1, y_2, y_3)\).
Table 2. Correlation coefficients of the main components of input and output.

| Input | Output 1 ($y_1$) | Output 2 ($y_2$) | Output 3 ($y_3$) |
|-------|------------------|------------------|------------------|
| $x_1$ | 0.820 **         | 0.363 **         | −0.208 **        |
| $x_2$ | 0.200            | 0.244 **         | 0.862 **         |
| $x_3$ (removed) | 0.182         | −0.194           | 0.195            |

Note: ** < 0.01.

4. Results and Discussion

4.1. Evaluation Results of Public Cultural Service Efficiency Based on a Super-Efficiency SBM

The scores of the positive principal components of 31 provinces in mainland China from 2013 to 2017 were introduced into the SBM model of super-efficiency, and the efficiency of public cultural services was calculated as shown in Table 3.

Table 3. Evaluation Results of the Super Efficiency slacks-based measure (SBM) Model of Public Cultural Services.

| Group | Province   | Region Belong to | 2013   | 2014   | 2015   | 2016   | 2017   | Average | Rank | GDP per Capita Ranking |
|-------|------------|------------------|--------|--------|--------|--------|--------|--------|------|------------------------|
| Group 1 | Anhui | Central | 0.923  | 0.987  | 0.952  | 1.135  | 1.541  | 1.108  | 1    | 26                     |
|       | Sichuan  | West          | 1.628  | 1.020  | 0.839  | 1.024  | 0.880  | 1.078  | 2    | 24                     |
|       | Henan    | Central       | 0.933  | 0.929  | 0.977  | 0.977  | 0.981  | 0.960  | 3    | 22                     |
|       | Hebei    | East          | 1.017  | 0.964  | 0.899  | 0.976  | 0.920  | 0.955  | 4    | 16                     |
|       | Hunan    | Central       | 0.974  | 1.008  | 1.027  | 0.887  | 0.879  | 0.955  | 5    | 17                     |

| Group 2 | Jiangsu | East         | 1.146  | 1.004  | 0.906  | 0.863  | 0.817  | 0.947  | 6    | 4                      |
|         | Guangdong| East         | 0.853  | 1.028  | 0.958  | 0.919  | 0.956  | 0.943  | 7    | 8                      |
|         | Xinjiang | West         | 0.893  | 0.882  | 1.003  | 0.999  | 0.939  | 0.943  | 8    | 18                     |
|         | Tibet    | West         | 0.966  | 0.945  | 0.928  | 0.902  | 0.886  | 0.925  | 9    | 28                     |
|         | Shanghai | East         | 0.832  | 1.218  | 0.905  | 0.953  | 0.715  | 0.924  | 10   | 3                      |
|         | Guizhou  | West         | 0.927  | 0.905  | 0.917  | 0.865  | 0.860  | 0.899  | 11   | 31                     |
|         | Guangxi  | West         | 0.894  | 0.946  | 0.861  | 0.825  | 0.849  | 0.875  | 12   | 27                     |
|         | Hainan   | East         | 0.848  | 0.856  | 0.856  | 0.878  | 0.908  | 0.869  | 13   | 21                     |
|         | Qihangai | West         | 0.880  | 0.854  | 0.857  | 0.841  | 0.831  | 0.853  | 14   | 19                     |
|         | Zhejiang | East         | 0.773  | 0.872  | 0.765  | 0.829  | 1.023  | 0.852  | 15   | 5                      |

| Group 3 | Jiangxi | Central       | 0.893  | 0.854  | 0.820  | 0.825  | 0.844  | 0.847  | 16   | 23                     |
|         | Ningxia  | West         | 0.860  | 0.854  | 0.830  | 0.821  | 0.830  | 0.839  | 17   | 15                     |
|         | Chongqing| West         | 0.771  | 0.776  | 0.813  | 0.831  | 0.951  | 0.828  | 18   | 12                     |
|         | Fujian   | East         | 0.824  | 0.837  | 0.778  | 0.764  | 0.849  | 0.810  | 19   | 7                      |
|         | Yunnan   | West         | 0.843  | 0.820  | 0.805  | 0.819  | 0.752  | 0.808  | 20   | 29                     |
|         | Gansu    | West         | 0.827  | 0.816  | 0.806  | 0.785  | 0.769  | 0.801  | 21   | 30                     |
|         | Shanxi   | Central       | 0.857  | 0.810  | 0.784  | 0.751  | 0.764  | 0.798  | 22   | 25                     |
|         | Liaoning | Northeast     | 0.857  | 0.830  | 0.742  | 0.753  | 0.776  | 0.791  | 23   | 9                      |

First, from the perspective of a longitudinal time series, from 2013 to 2017, the average public cultural service efficiency in China’s 31 provinces showed a downward trend. From 2013 to 2017, the average value of the public cultural service efficiency in 31 provinces was 0.847. The average efficiency value in 2013 was 0.872; however, the value in 2017 was reduced to 0.839, with a 4% drop compared with that in 2013. Compared to 2013, 22 out of the 31 provinces had reduced efficiency (accounting for 71%), and the other 9 provinces had increased efficiency (accounting for 29%) in 2017. As the influence of price rise was eliminated, it can be concluded that the utilization level of China’s public cultural resources was going down.
Second, from a horizontal perspective, there are significant differences in the efficiency of the public cultural services in different provinces of China. From 2013 to 2017, the average annual efficiency of public cultural services in the 31 provinces was between 0.617 and 1.108, and there was a big difference between different provinces. According to the annual average efficiency index, 31 provinces were divided into 4 groups. The first group had average efficiency values greater than 0.95 and included Anhui, Sichuan, Henan, Hebei, and Hunan (5 provinces). The second group had average efficiency values of 0.85–0.95, including Jiangsu, Guangdong, Xinjiang, Tibet, Shanghai, Guizhou, Guangxi, Hainan, Qinghai, and Zhejiang (10 provinces). The provinces in the third group had average efficiency values ranging from 0.75 to 0.85, including Jiangxi, Ningxia, Chongqing, Fujian, Yunnan, Gansu, Shanxi, and Liaoning (8 provinces). The fourth group had average efficiency values less than 0.75, including Tianjin, Inner Mongolia, Jilin, Shandong, Heilongjiang, Hubei, Shaanxi, and Beijing (8 provinces). The provinces presenting effective SBM were Anhui and Sichuan, while Beijing had the lowest efficiency. The geographical distribution is shown in Figure 1.

Third, according to Table 3, we further collated the average values of the SBM efficiency of public cultural services in the provinces of the eastern, central, western, and northeastern regions and the average annual public cultural service efficiency of various regions from 2013 to 2017 (see Table 4). It can be seen that the gap in the efficiency of public cultural services in the four regions is also obvious. This is also reflected in Figure 1. The average annual efficiency values of the four regions from high to low are central, west, east, and northeast, and the corresponding average efficiency values are 0.894, 0.853, 0.840, and 0.751, respectively. Moreover, from 2013 to 2017, the average efficiency value of the provinces in the eastern region briefly increased in 2014, then fell sharply in 2015, and then slowly increased. The efficiency value in 2017 was significantly lower than that in 2013; the average efficiency value in the western and northeastern regions showed a significant downward trend, and only the central region showed a relatively obvious upward trend. Judging from the standard deviation of the

![Figure 1. Efficiency distribution of China’s public cultural services based on the SBM model of super-efficiency.](image-url)
provincial average efficiency of each region each year, the efficiency gap of public cultural services in
the various regions from 2013 to 2017 has increased year by year.

Table 4. The average value of public cultural service efficiency by province in the four major regions.

|        | 2013   | 2014   | 2015   | 2016   | 2017   | Annual Average |
|--------|--------|--------|--------|--------|--------|----------------|
| East   | 0.842  | 0.892  | 0.817  | 0.823  | 0.824  | 0.840          |
| Central| 0.883  | 0.884  | 0.874  | 0.881  | 0.949  | 0.894          |
| West   | 0.913  | 0.854  | 0.840  | 0.839  | 0.821  | 0.853          |
| Northeast| 0.789 | 0.776  | 0.727  | 0.724  | 0.738  | 0.751          |
| Std. Dev.| 0.054  | 0.053  | 0.063  | 0.066  | 0.087  |                |

Fourth, from 2013 to 2017, the changes in the efficiency of public cultural services in the 31
provinces in China were quite different. Figure 2 presents box plots of the public cultural service
efficiency in the 31 provinces, reflecting the efficiency changes in each province. Provinces with
larger standard deviations include Sichuan, Anhui, Shanghai, Jiangsu, and Zhejiang. The efficiency
of the public cultural services in Anhui and Zhejiang was greatly improved; however, in Sichuan and
Shanghai, the efficiency showed an obvious downward trend in fluctuations. The efficiency in Jiangsu
has been showing a downward trend. The standard deviation in most other provinces was not large.
Combined with Table 3, the efficiency of the public cultural services in most provinces slowly declined.

4.2. Discussion on the Influencing Factors of Public Cultural Service Efficiency

Based on the SBM model of super-efficiency, the public cultural service efficiencies in China’s 31
provinces from 2013 to 2017 were calculated. We found significant differences in the service efficiencies
of different provinces in different years. We used the panel data model to discuss the influencing factors of public cultural service efficiency, as well as their degrees of influence.

4.2.1. Variable Selection and Data Description

Based on the existing literature, five main factors affecting the efficiency of public cultural services were selected as explanatory variables.

(1) GDP per capita \((rgdp)\). In this paper, the GDP per capita of each province is the real value converted through the price index using 2013 as the base period, which can reflect the economic development level of each province. Current studies generally believe that the economic development level is one of the important factors affecting the efficiency of public cultural services; however, different researchers have different opinions on the specific impact characteristics. The research results of Yang et al. [25] and Han et al. [26] showed that the economic development level is negatively correlated to the efficiency of public cultural services, while Wang et al. [23] argued that the economic development level plays a significant role in promoting the efficiency of public cultural services.

(2) Financial support \((attention)\). This paper uses the proportion of cultural undertaking expenditures in the fiscal expenditures to measure the government’s financial support of public cultural services, which also reflects the government’s emphasis on public cultural services. In general, the government’s emphasis on public cultural services will help improve service efficiency. However, excessive government expenditures without proper supervision can easily result in the waste of public cultural resources, resulting in a reduction of service efficiency.

(3) Fiscal decentralization \((finance)\). This paper references the research of Chen et al. [33] and employs the ratio of the general budget revenue to the general budget expenditure of local governments to measure the degree of fiscal decentralization, which also reflects the degree of the fiscal autonomy of local governments. Local governments with higher fiscal autonomy have competitive advantages [34], thereby improving the usage efficiency of fiscal funds. However, Fu [35] argued that fiscal decentralization “reduces the supply efficiency of non-economic public goods”. Therefore, the impact of fiscal decentralization on the efficiency of public cultural services may also be negative.

(4) Population density \((density)\). This is expressed in thousand people per square kilometer. The research results of Lai [36] showed that population density is positively correlated to the efficiency of public cultural services. With a larger population density, public cultural services can cover a larger number of people. Therefore, it is easy to form scale effects and improve the efficiency of public cultural services. However, Shen et al. [27] argued that a larger population density may yield scale effects but less public cultural services per capita. There will be a great loss of efficiency when the supply form and quality of public cultural services cannot meet the needs of most people.

(5) Average years of schooling \((edu)\). In the China Statistical Yearbook, the education level of the population aged 6 and above was counted. The average years of education in this paper were calculated using Equation (4), which indicates the education level of the residents in a certain area. On one hand, the improvement of the residents’ education level may increase demand for public culture and have a positive impact on the efficiency of public cultural services. On the other hand, it may also increase people’s demand for “private culture,” which will in turn decrease the demand for “public culture” and reduce the efficiency of public cultural services [37].

\[
\text{Average years of schooling} = (\text{population with no schooling} \times 0 + \text{population at primary school level} \times 6 + \text{population at junior high school level} \times 9 + \text{population at senior high school level} \times 12 + \text{population at junior college level and above} \times 16)/\text{total population aged 6 and above} \tag{4}
\]

4.2.2. Descriptive Statistics of the Variables and Selection of the Panel Data Model

This paper uses the panel data for 31 provinces in China from 2013 to 2017. The data source was the China Statistical Yearbook (2014–2018). Some data were obtained through necessary calculations,
and the accuracy and reliability of the data can be guaranteed. The descriptive statistics of all variables are shown in Table 5.

Table 5. Descriptive statistics of variables.

| Variable | Mean | Std. Dev. | Min  | Max  |
|----------|------|-----------|------|------|
| gwv      | 0.847| 0.140     | 0.596| 1.628|
| rgdp     | 54.568| 23.903    | 23.151| 125.848|
| attention| 0.443| 0.110     | 0.260| 0.788|
| finance  | 49.944| 19.835    | 9.368| 93.137|
| density  | 0.457| 0.699     | 0.003| 3.851|
| edu      | 9.073| 1.155     | 4.222| 12.502|

The F test results strongly rejected the original hypothesis that “mixed regression was acceptable,” suggesting that the fixed effects were better than the mixed effects. Through the LM test, it was found that the results strongly rejected the original hypothesis that “there were no individual random effects.” Therefore, we chose random effects instead of mixed effects. The Hausman test showed that the P value was 0.1417 > 0.05; thus, the random effects model was selected instead of the fixed effects model. Equation (5) provides the regression equation.

\[ gwv_{it} = \alpha + \beta_1 rgdp_{it} + \beta_2 attention_{it} + \beta_3 finance_{it} + \beta_4 density_{it} + \beta_5 edu_{it} + v_{it} \]  

(5)

where, \( gwv_{it} \) represents the calculated efficiency value of the public cultural services in each province of China from 2013 to 2017, \( rgdp_{it}, attention_{it}, finance_{it}, density_{it}, \) and \( edu_{it} \) represent the GDP per capita (thousand yuan), fiscal support (%), fiscal decentralization (%), population density (thousand people), and average years of schooling (years) for each province in China from 2013 to 2017, and \( v_{it} = \gamma_i + \epsilon_{it} \) is a random disturbance term.

4.2.3. Discussion of the Regression Results

The statistical software stata15 was used to conduct a regression analysis on the above random effects model of panel data, and the estimated parameters are shown in Table 6. Most variables passed the significance test, except for financial support. More details are discussed below.

Table 6. Regression results of the random effects model.

| Variable | Coef. | Robust Std. Err | Wald |
|----------|-------|-----------------|------|
| rgdp     | -0.0020737 * | 0.0010787 | 43.76 *** |
| Attention| -0.0365625  | 0.1077621 | 0.000035 |
| Finance  | 0.002038 *  | 0.0010753 | 0.000035 |
| Density  | 0.0575937 ***| 0.0116903 | 0.000035 |
| Edu      | -0.0457964 ***| 0.0152006 | 0.000035 |

Note: *, **, *** indicate passing a significance level test of 10%, 5%, and 1%, respectively.

The GDP per capita has a negative correlation with the efficiency of public cultural services at a significant level of 10%, which is consistent with the findings of Yang et al. [25] and Han et al. [26]. There are two possible reasons for this result. Firstly, in developed areas, there is a tendency to pay more attention to economy than culture. Secondly, the disposable income per capita in developed areas is also higher, and people have more diversified cultural needs in addition to low-cost or free public cultural services.
Fiscal decentralization passed the test with a positive coefficient at a 10% significance level. This indicates that fiscal decentralization has a significant positive impact on the efficiency of public cultural services, which is consistent with the views of Han et al. [26] and Chapman [34]. The efficiency of public cultural services is higher in regions with higher fiscal autonomy.

Population density passed the test at a 1% significance level with a positive coefficient, indicating a significant positive correlation between the population density and the efficiency of public cultural services. This result is consistent with the conclusions of Lai [36], that it is easy to form scale effects on the use of public cultural resources and improve the efficiency of public cultural services in regions with a larger population density.

The average years of schooling are negatively correlated to the efficiency of public cultural services at a 1% significance level. This is consistent with the findings of Wu et al. [37] that the improvement of education level will lead to an increase in people’s demands for “private culture” and reduce the demand for “public culture.”

5. Conclusions and Policy Recommendations

Based on an evaluation of the super-efficiency SBM model of China’s public cultural services from 2013 to 2017, and using panel data models to discuss and analyze the main factors affecting the efficiency of public cultural services, this paper draws the following conclusions:

First, from the perspective of longitudinal time series, the average efficiency of the public cultural services in 31 provinces in China shows a downward trend from 2013 to 2017.

Second, from a horizontal perspective, there are significant differences in the efficiency of the public cultural services in different provinces and regions of China.

Third, the GDP per capita and average years of schooling have a significant negative impact on the efficiency of public cultural services. Fiscal decentralization and population density have a significant positive impact on the efficiency of public cultural services.

Based on the above research conclusions, we offer three main policy recommendations. First, with the economic development and the improvement of average education level, the government should optimize the input structure of public cultural services, adjust their service direction, and improve the matching accuracy of service supply and demand to satisfy more diversified and personalized public cultural needs. Secondly, the panel data model discussion showed that there is a significant negative correlation between the efficiency of public cultural services and the level of economic development. In other words, the efficiency of public cultural services in underdeveloped areas is higher than that in developed areas. Therefore, we suggest that related policies should be formulated in order to adjust the allocation of public cultural resources nationwide and facilitate the flow of public cultural resources from developed areas to underdeveloped areas (i.e., from low-efficiency provinces to high-efficiency provinces). Thirdly, the degree of fiscal decentralization has a significantly positive correlation with the efficiency of public cultural services, and local fiscal autonomy contributes to the improvement of public cultural service efficiency. Therefore, we suggest to further improve the reform of the fiscal decentralization system, transform large-scale transfer payments into higher financial autonomy for the local government, and appropriately introduce the PPP model to utilize private capital to improve the efficiency of local governments’ public cultural services.

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