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Analyzing the Shift in China's Cultural Industries: From Economic Growth to Social Enrichment

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Abstract: Cultural industries constitute a crucial part of the sustainable economy. In accordance with the principles of socialist public ownership nations, the economic benefits of cultural industries should be ultimately transformed into more significant social benefits. Guided by the policies and requirements of the Chinese government concerning the social benefits of cultural industries, this paper innovatively integrates Data Envelopment Analysis (DEA) and Tobit models to empirically analyze the social benefits and their influencing factors within China's cultural industries. The findings indicate that the social benefits of China's cultural industries are currently in a state of diminishing returns to scale, with fiscal support and educational levels significantly enhancing the industry's social benefits. This paper recommends that policymakers aiming to convert the economic benefits of cultural industries into social benefits more systematically and effectively should focus on enhancing the quality of industry outputs.

Keywords: sustainability; cultural industries; social benefits; DEA; PCA; Tobit

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1. Introduction

1.1. Characteristics of China's Culture Industries

Cultural industries, as a facet of the sustainable economy, represent a critical element for sustainable development. Vila et al. [1] observed, in their examination of European Union cultural policies, that eight of the seventeen Sustainable Development Goals defined by the United Nations encompass interdisciplinary themes involving culture. The research conducted by Duxbury et al. [2] highlighted the significant role cultural industries can play in areas such as safeguarding cultural rights and fostering ecological citizenship, which are pivotal for sustainability.

China, with its mixed economic system that accommodates both public and private sectors, delineates its cultural industries to include nine broad categories: news and information services, content creation and production, creative design services, cultural dissemination channels, cultural investment and operations, cultural entertainment and leisure services, support production and intermediary services for culture, cultural equipment manufacturing, and the production of cultural consumption terminals [3]. A substantial portion of these sectors are state-owned and operated under unified management. For instance, due to the characteristics of the public sector, all land ownership related to the cultural industries, including tourist attractions, sports and arts venues, and hotels, is nationalized. Moreover, in pursuit of public opinion oversight, virtually all broadcasting stations, television stations, and publishing houses, as channels of cultural communication, are under state ownership.

In summary, the Chinese government places a high value on the societal impact generated by cultural industries. Therefore, the evaluation of cultural industries extends beyond economic indicators to encompass the reflection of social values.

1.2. Social Benefits of China's Culture Industries

This study posits that the social impact of cultural industries primarily encompasses two major aspects. The first pertains to the extent of the cultural industries' influence on the value orientation of the populace. Conducting empirical research in this area is challenging, necessitating extensive tracking and data analysis over a significant period across a large sample population to derive objective results.

The second aspect concerns the social benefits of the cultural industries beyond their economic contributions. In support of cultural industry projects, the Chinese government establishes social benefit assessment criteria at the inception stage, typically including the number of job opportunities created, taxes paid, cultural venues established, works completed, and the extent of service provision to the public. Notably, such social benefit requirements are not exclusive to cultural industries' projects but are also prevalent in the assessment of support projects in other sectors, significantly influencing the final evaluation of these initiatives. This focus on social benefits, amenable to empirical investigation through operations research and econometric methods, is a central concern of this study.

Despite the significant emphasis on the societal impact of the cultural industries within China, previous academic research has predominantly focused on its economic benefits. For instance, a study by Zeng et al. [4] primarily addresses the economic contributions of the cultural industries. Similarly, a comparative analysis conducted by You et al. [5] on the cultural industries of China and South Korea concentrates on assessing the economic benefits within these two nations. Research by Zhou et al. [6] explores the economic benefits of the cultural industries while merely touching upon its impact on employment opportunities, a single aspect of social benefits. More recent investigations by Qi et al. [7] continue to revolve around the economic benefits derived from the cultural industries. Furthermore, even when the Chinese government evaluates the projects it supports, the assessment often remains limited to whether specific indicators meet established standards, with a significant lack of comprehensive evaluation concerning social benefits.

1.3. Research Objectives

In light of the foregoing, this study asserts the following: firstly, the social benefits of cultural industries are crucial to human well-being, especially in states with predominant public ownership, where their importance may surpass economic benefits; secondly, comprehensive research on the social benefits of cultural industries remains markedly scarce; and thirdly, the study of the social benefits of cultural industries can employ empirical research methodologies. Therefore, this paper sets forth the following research objectives:

1. To employ empirical methods from operations research and econometrics in investigating the benefits of cultural industries.
2. To conduct a comprehensive evaluation of the social benefits of China's cultural industries, incorporating actual data from government policies for correlational studies.
3. To discuss the experiences and challenges in assessing the social benefits of China's cultural industries.

It is imperative to recognize that assessments of the social benefits of China's cultural industries often differ significantly from conventional economic evaluations. For instance, factors such as tax contributions and employment figures, typically considered inputs and indicative of lower economic efficiency when higher in economic assessments, are viewed as outputs in social benefit evaluations, with larger figures denoting greater contributions to society.

The ultimate aim of this study is to utilize the social benefits of China's cultural industries as a case study to delineate a methodological framework for researching the social benefits of cultural industries from the perspective of human well-being. This framework could also be applicable to other regions and industries, suggesting that in formulating policies for foundational industries of a country or region, considerations should extend beyond economic benefits to include the social benefits they confer.

This study holds significant implications for sustainable economies and societies. The methodology and outcomes offer policymakers and cultural industry managers a novel perspective, paving the way for the optimization of cultural industries to enhance its dual role in promoting social welfare and economic growth. Through empirical methods, this study comprehensively assesses the social benefits of cultural industries, examining factors that influence these benefits. This enables the development of targeted and comprehensive intervention measures to strengthen the social and economic contributions of the cultural industries. More broadly, the approach used in this study can be applied to the evaluation of other industries and the formulation of relevant policies, thereby extending its utility to a wider range of sectors.

2. Materials and Methods

2.1. Research Process

The research methodology employed in this paper is delineated as follows:

1. Collection of various data on cultural industries publicly issued by the Chinese government.
2. Conducting a comprehensive evaluation of the social benefits of China's cultural industries based on the collected data.
3. Analyzing the correlation between the comprehensive assessment results of the social benefits of the cultural industries and the variables that may influence them.
4. Discussing and investigating these findings.

The entire process is illustrated in Figure 1.

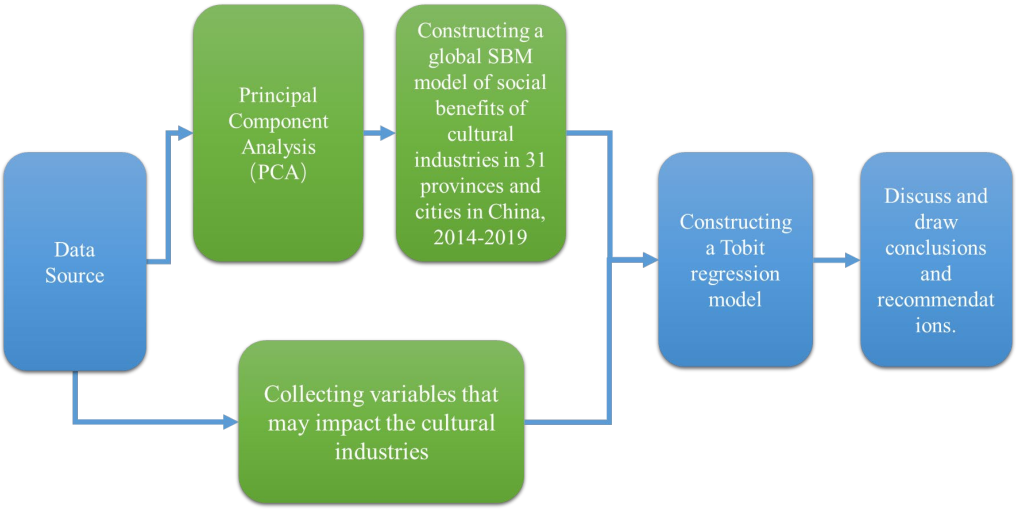

Figure 1. Research flowchart of the social benefits of the cultural industries in 31 provinces of China from 2014 to 2019.

2.2. Methods

In this paper, the method chosen to assess the social benefits of China's cultural industries is efficiency evaluation, which focuses on achieving more outputs with fewer inputs, making it well suited for assessing the comprehensive ability of industries to generate benefits. Specifically, the Data Envelopment Analysis (DEA) method is employed. DEA is used to assess the efficiency of entities known as Decision-Making Units (DMUs) by comparing their input–output ratios to those of the best performers, creating a benchmark or "envelope". A key feature of DEA is that it does not require a predetermined form of the production function, nor does it require predetermined weights for the input and output indicators, allowing it to handle multiple inputs and outputs and to identify and evaluate the efficiency of each DMU. The DEA method was proposed by Charnes, Cooper, and Rhodes [8]. Its core concept involves constructing an envelopment surface from the best-performing DMUs in the dataset to evaluate other DMUs. DMUs on the envelope are considered efficient, while those below the envelope are deemed inefficient, as their input and output combinations fall short compared to those on the envelope. By examining these discrepancies, specific targets and pathways for improvement can be identified, providing valuable management insights for decision-makers. Due to these advantages, the DEA method is widely applied in various fields, including efficiency assessments in education, healthcare, energy, banking, and other industries.

The initial DEA models were the CCR model, introduced by Charnes, Cooper, and Rhodes, based on the assumption of constant returns to scale (CRS), and the BCC model [9], introduced by Banker, Charnes, and Cooper, based on variable returns to scale (VRS). These models allowed for proportional changes in input or output variables but did not account for improvements in individual inputs or outputs. Tone introduced the Slack-Based Measure (SBM) model [10], which focuses on slacks in individual variables, providing an empirical basis for individual variable improvement. This marked a shift in DEA methodology from focusing on a single efficiency type to evaluating comprehensive efficiency. The SBM model represents a significant theoretical and practical advancement in DEA methodology, offering a more sophisticated and comprehensive tool for assessing and enhancing the efficiency of organizations and industries.

The SBM model has been widely applied in various studies. Chiu et al. [11] utilized the SBM super-efficiency model to assess the efficiency and risk of Taiwanese banks. Yang and Li [12] applied the DEA-SBM model to evaluate the efficiency of water resource utilization. Choi et al. [13] used the DEA-SBM model to assess the sustainable performance of the Korean steel industry. In the realm of cultural industries, Wang and Chen [14] employed the SBM model to evaluate the service efficiency of the public cultural sector. Gao et al. [15] also used the SBM model in their study on the spatiotemporal patterns of tourism efficiency in Chinese provinces.

The SBM model has three orientations: input-oriented, defined as minimizing inputs without changing the quantity of outputs; output-oriented, defined as maximizing outputs without changing the inputs; and non-oriented, which considers the optimization of both inputs and outputs. Given that the focus of this study is on the efficiency of the social benefits of China's cultural industries, typically assessed based on the quantity of outputs, the output-oriented SBM model is deemed most appropriate. The formula for the output-oriented SBM model is as follows [16]:

The output-oriented SBM efficiency ρ_o^* of $DMU_o = (x_o, y_o)$ is defined by [SBM-O-C].

Objective Function:

$$\frac{1}{\rho_o^*} = \min_{\lambda, s^-, s^+} 1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}},$$

Subject to the following:

$$x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \ (i = 1, \ldots, m)$$

$$y_{io} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \ (r = 1, \ldots, s)$$

$$\lambda_j \geq 0(\forall j), \ \ s_i^- \geq 0(\forall i), \ \ s_r^+ \geq 0(\forall r)$$

wherein

s_i^- and s_r^+ denote slack variables for inputs and outputs.
x_{ij} and y_{rj} represent the ith input and rth output of the jth DMU, respectively.
m and s are the number of inputs and outputs, and n is the number of DMUs.

ρ in the objective function is the efficiency score, bounded within the interval [0, 1].

The conventional SBM model employs cross-sectional data for model construction, with efficiency scores representing relative performance among DMUs within a specific period, rendering direct comparisons across different periods infeasible. Although many studies have utilized the DEA–Malmquist index model to analyze panel data, facilitating trend analysis, the outcomes of the DEA–Malmquist index model are indices rather than efficiency scores, which limits their utility in subsequent correlational analyses. Furthermore, the DEA–Malmquist index model frequently encounters issues of infeasibility, obstructing the progression of research.

In response to these challenges, Golany and Roll [17] proposed the Global DEA model, which considers the data from DMUs across all periods as a single reference set for model construction. This approach allows the efficiency scores to encapsulate the effects of time series, enabling longitudinal comparisons of efficiency scores for the same DMU across different periods. This method circumvents the issue of infeasibility encountered with the Malmquist index model. Moreover, like the standard SBM model, the Global DEA model allows for decomposition, providing better interpretability, flexibility, and suitability for further extended research.

A limitation of the DEA model is that the number of DMUs should be at least three times greater than the total number of input and output variables to ensure the model's effectiveness and accuracy [16]. However, in assessing the social benefits of China's cultural industries, given the industry's broad scope and the numerous output variables involved, which cannot be arbitrarily omitted, this paper employs Principal Component Analysis (PCA) to reduce the dimensionality of the numerous output variables. PCA is a statistical method used to reduce the dimensionality of data while retaining as much of the original data's significant information as possible. It achieves this by identifying and extracting the principal components, which are the main information carriers within the data, and transforming the original variables into a new set of orthogonal variables. These new variables capture the majority of the variability in the original dataset. The dimensionality-reduced data can reflect core information in a more focused manner, thus enabling DEA analysis to proceed without sacrificing too much information.

The use of PCA for variable reduction in DEA models was initially proposed by Cinca et al. in 2004 [18]. Adler and Yazhemsky further refined this approach in their research [19], and it has since been applied in numerous DEA analyses. Jothimani et al. used the PCA-DEA method to establish a stock selection framework for the Indian stock market [20]. Stević et al. employed it to assess the efficiency of transport companies [21].

It is important to note that not all datasets are suitable for dimensionality reduction using the PCA method. Prior to conducting PCA, it is essential to perform the Kaiser–Meyer–Olkin (KMO) and Bartlett's Test of Sphericity. The KMO measure, which assesses the suitability of data for PCA, is considered adequate for PCA if the value exceeds 0.6. During Bartlett's Test of Sphericity, a p-value less than 0.05 indicates the data are likely suitable for PCA.

Due to the potential presence of negative values and significant scale differences between the input variables and the data reduced through PCA, it was necessary to standardize all input and output variables prior to conducting Data Envelopment Analysis (DEA). This standardization was performed using the MIN-MAX normalization method, which is described by the following formula:

The MIN-MAX normalization formula is designed to rescale features to lie in a given range, typically between 0 and 1. The formula is as follows:

$$z = \frac{(x - x_{min})}{(x_{max} - x)}$$

where

z is the normalized value.

x is the original data value.
x_{min} is the smallest value in the dataset.
x_{max} is the largest value in the dataset.

After applying this formula, the data values are transformed to fall within the range of 0 to 1.

After constructing the Global SBM model for the social benefits of the cultural industries, an exploration of the reasons behind the model's efficiency scores necessitates a correlation analysis. The primary method for this correlation study is regression analysis, using the efficiency scores from the Global SBM model as the dependent variable and data on relevant policies from the Chinese government collected during the study period as independent variables to construct the regression model. Compared to other DEA models that only provide efficiency scores for a single period, the Global SBM model, which references data from all periods for each efficiency score, is better suited for regression analysis with the time series data of the independent variables.

Among various regression analyses, the Tobit regression is most apt for DEA efficiency scores, as these scores range between 0 and 1. The Tobit regression model [22] employs the maximum likelihood estimation technique and is a linear regression model particularly suited for handling dependent variables subject to censoring. The mathematical representation of the Tobit model is as follows:

$$y_i^* = \beta X_i + \varepsilon_i$$

where

y_i^* is the latent (unobservable) variable that represents the true value of the dependent variable.
β is a vector of coefficients.
X_i is a vector of independent variables.
ϵ_i is the error term, typically assumed to be normally distributed with mean zero and variance σ^2.

Kirjavainen et al. [23] utilized a combination of DEA and Tobit models to study the efficiency of Finnish high schools. Similarly, Fethi et al. applied the DEA-Tobit model to examine the efficiency of European airlines [24]. Additionally, studies by Grmanová & Strunz [25], Guo et al. [26], and Istaiteyeh et al. [27] have also employed the DEA-Tobit model combination. In the cultural industries sector, Liu et al. [28] used this model combination in their research on coastal ecotourism in China, Tu et al. [29] in their study of the cultural services industry, and Liu [30] in his investigation of rural public cultural services.

In this study, the DEA model was constructed using DEARUN software (DEARUN v3.2.0.2 Trial), while PCA and the development of the Tobit model were carried out using the SPSSAU online analysis software. Both software tools feature user-friendly, fully graphical interfaces with built-in common models, eliminating the need for user-generated code input. The outputs are clear and standardized, accompanied by explanations and analytical recommendations.

2.3. Data

In this study, 31 out of 34 provincial-level administrative units in China were selected as research subjects. Taiwan, Hong Kong, and Macau were not included due to significant differences in political systems and management policies. For instance, in Hong Kong, the tourism industry, cultural and creative industries, and the news and entertainment sectors are managed by different departments, making it challenging to collect comprehensive data. The statistical data reported to China's Ministry of Culture and Tourism from Hong Kong only include aspects of the cultural and creative industries.

The period selected for this study spans from 2014 to 2019. Earlier periods were not included due to differences in statistical calibrations, and data post-2019 were excluded due to significant changes in China's cultural industries influenced by COVID-19. From 2020 to 2022, the Chinese government implemented stringent containment measures in response to the pandemic, resulting in theatres, cinemas, internet cafes, tourist attractions, and other venues being closed for the majority of this time. Therefore, data from this period were not considered in this study to avoid excessive interference with the research objectives. Future studies will specifically explore the impact of COVID-19 on the cultural industries.

All monetary values in the dataset, denominated in Renminbi (RMB), have been adjusted according to the respective annual price indices to reflect constant prices as of the end of 2019. It is important to note an anomaly in the visitor numbers to Grade A tourist attractions in Tibet in 2016, which showed an increase of more than tenfold compared to the years 2015 and 2017. Upon verification from multiple sources, it was found that there were significant errors in the 2016 annual report of the Tibet Tourism Co., Ltd, Lasa, China [31]. Therefore, this data were not adopted in this study. Instead, a linear interpolation method was used to calculate a substitute value.

3. Results

3.1. PCA

In constructing the SBM model, it is essential to identify appropriate input and output variables. In a socialist public ownership state, the concept that state assets and profits are utilized for the public good, with political benefits taking precedence over economic ones, as revealed by Chan [32], plays a crucial role. Hence, the selection of input and output variables shows significant differences. This study selects two input variables: Total Assets in cultural industries and the current Total Revenue of cultural industries. Although Total Revenue is typically treated as an output variable in conventional economic efficiency assessments, in our study, it is considered an input contributing to social benefits.

In terms of output variables, Section 1.2 of this paper mentioned that China's cultural industries comprise nine major parts; hence, thirteen output variables were selected to represent these nine components:

- Engaged Persons at Year-end measures the total employment opportunities provided by the cultural industries, indicating their capacity to generate jobs.
- Total Tax is utilized to quantify the total tax revenue generated by the cultural industries. While taxes are often considered costs in economic evaluations, they are treated as outputs in social benefit assessments.
- Per capita wage measures the income provided to individuals employed within the cultural industries, reflecting the sector's ability to support its workforce.
- Production and Transaction of TV Program, Production and Transaction of Radio Program, and Registration of Original Product are indicators used to measure the volume of cultural products within news and information services, content creation and production, creative design services, and cultural dissemination channels.
- Granted Patent Applications on culture industries assesses the innovative capacity of the cultural industries, indicating their contribution to technological and creative advancements.
- Number of Visitors to Tourist Attractions reflects the number of visitors to provincial and municipal A-grade scenic spots as rated by the National Tourism Administration, measuring the service and benefits provided by the tourism sector.
- Number of Overseas Visitor Arrivals is used to evaluate the international social impact generated by the tourism industry.
- Museum Spectators measures the societal impact created by various museums, indicating cultural engagement and educational outreach.
- Spectators of Agencies of Cultural Relics Preservation assesses the social impact of traditional China's culture through visitor numbers at key heritage sites, such as the Forbidden City and Mogao Caves.
- Domestic Audience Numbers for Art Performance Troupes measures the social impact of Chinese art performance groups, including Peking opera troupes and orchestras.

- Attending Art and Cultural Activities represents the number of participants in folk arts and cultural activities, encompassing not only spectators but also amateur performers.

All input and output variables are listed in Table 1.

Table 1. Input and output variables for the social benefit model of China's cultural industries.

Indicator Categories	Indicators
Input indicators	Total Assets
	Total Revenue
output indicators	Engaged Persons at Year-end
	Total Tax
	Per capita wage
	Production and Transaction of TV Program
	Production and Transaction of Radio Program
	Registration of Original Product
	Granted Patent Applications on cultural industries
	Number of Visitors to Tourist Attractions
	Number of Overseas Visitor Arrivals
	Museum Spectators
	Spectators of Agencies of Cultural Relics Preservation
	Domestic Audience Numbers for Art Performance Troupes
	Attending Art and Cultural Activities

In this study, the SPSSAU software (SPSSAU v24.0) was utilized to perform PCA for dimensionality reduction on 13 output variables. Initially, the KMO test and Bartlett's Test of Sphericity were conducted to assess the appropriateness of PCA for the data. The results, as shown in Table 2, revealed a KMO value of 0.762 for the 13 variables, exceeding the recommended threshold of 0.6. Furthermore, the p-value for Bartlett's Test of Sphericity was less than 0.05, indicating that the data are highly suitable for PCA.

Table 2. KMO test and Bartlett's Test of Sphericity.

KMO and Bartlett Sphericity Test		
KMO		0.762
Bartlett sphericity test	Approximate Chi-square	2645.646
	df	78
	p	0.000

The variance explained by the PCA in this study is detailed in Table 3. A total of three principal components with eigenvalues greater than 1 are extracted. The variance explained by these three principal components is 48.401%, 18.378%, and 12.070%, respectively, cumulating to a total explained variance of 78.849%.

Table 4 illustrates the information extraction of each output variable by the principal components and the corresponding relationship between the principal components and the research items. The communality values for all output variables are higher than 0.6, exceeding the general requirement of 0.4. This indicates a strong association between each output variable and the principal components, demonstrating that the PCA effectively extracts information from the output variables.

Table 3. Variance explained in PCA.

	Eigen Root			Principal Component Extraction		
	Eigen Root	Variance Explained (%)	Cumulative (%)	Eigen Root	Variance Explained (%)	Cumulative (%)
1	6.292	48.401	48.401	6.292	48.401	48.401
2	2.389	18.378	66.779	2.389	18.378	66.779
3	1.569	12.070	78.849	1.569	12.070	78.849
4	0.795	6.118	84.967	-	-	-
5	0.570	4.382	89.350	-	-	-
6	0.513	3.944	93.294	-	-	-
7	0.300	2.308	95.602	-	-	-
8	0.191	1.472	97.074	-	-	-
9	0.141	1.082	98.156	-	-	-
10	0.090	0.694	98.850	-	-	-
11	0.076	0.587	99.437	-	-	-
12	0.037	0.287	99.724	-	-	-
13	0.036	0.276	100.000	-	-	-

Table 4. Loadings in PCA.

	Loading Factor			Commonality (Common Factor Variance)
	PCA1	PCA2	PCA3	
Production and Transaction of TV Program	0.858	−0.109	−0.026	0.749
Production and Transaction of Radio Program	0.829	−0.315	−0.065	0.791
Granted Patent Applications on cultural industries	0.820	0.072	−0.440	0.871
Number of Visitors to Tourist Attractions	0.828	−0.092	0.283	0.774
Number of Overseas Visitor Arrivals	0.664	0.055	−0.659	0.878
Museum Spectators	0.804	−0.287	0.238	0.786
Spectators of Agencies of Cultural Relics Preservation	0.559	−0.017	0.622	0.699
Registration of Original Product	0.318	0.857	0.232	0.889
Attending Art and Cultural Activities	0.862	−0.203	−0.011	0.784
Domestic Audience Numbers for Art Performance Troupes	0.368	−0.341	0.497	0.499
Per capita wage (yuan)	0.223	0.820	−0.044	0.724
Engaged Persons at Year-end	0.910	0.029	−0.262	0.897
Total Tax	0.504	0.783	0.205	0.910

In summary, the results of this PCA indicate that three principal components were extracted, and the test results demonstrate that these components effectively represent the 13 output variables. The input–output data table used for constructing the social benefit model of China's cultural industries across 31 provinces from 2014 to 2019 can be found in the Supplementary Material, Table S1.

3.2. Construction of the Global SBM Model for Cultural Industries in 31 Provinces of China, 2014–2017

After adjustments based on PCA, the input–output variables used for DEA analysis are presented as shown in Table 5.

Table 5. Input–output variables for constructing the Global SBM model after PCA analysis adjustment.

Indicator Categories	Indicators
Input indicators	Total Assets
	Total Revenue
output indicators	PCA1
	PCA2
	PCA3

This study employed the DEARUN software to construct an output-oriented Global SBM model for China's cultural industries from 2014 to 2019. The aggregated scores of the model are presented in Table 6.

Table 6. Summary of the Global SBM model for social benefits of China's cultural industries, 2014–2019.

	Mean Value of TE	Mean Value of PTE	Mean Value of SE	Number of DRS	Number of IRS	Number of CRS
2014	0.553187223	0.707102526	0.772121474	25	3	3
2015	0.531712378	0.701887355	0.74713103	26	2	3
2016	0.534614492	0.718353406	0.730547073	24	3	4
2017	0.519257223	0.709444514	0.722439988	26	1	4
2018	0.546646427	0.762846347	0.711974004	26	1	4
2019	0.56806787	0.807803125	0.708881076	24	2	5

In Table 6, the "Mean value of TE" represents the average technical efficiency (TE) scores of the 31 provinces and cities, which is the mean efficiency score under the assumption of CRS. The "Mean value of PTE" denotes the average pure technical efficiency scores (PTE) of the 31 provinces and cities, also the average under the assumption of VRS. "SE" indicates the mean scale efficiency scores of the 31 provinces and cities. "Number of DRS" refers to the number of provinces and cities operating under decreasing returns to scale, while "Number of IRS" indicates those under increasing returns to scale, and "Number of CRS" denotes those operating under constant returns to scale. For the complete Global SBM model, please refer to Table S2 in the Supplementary Material.

3.3. Construction of Tobit Model for Influencing Factors of Social Benefits in China's Cultural Industries

To investigate the influencing factors of social benefits in China's cultural industries, this study selected five independent variables: Proportion of Urban Population, representing the urban population ratio in each province; Degree of financial support, indicating the financial support from provincial governments to the cultural industries, measured as the proportion of expenditures on cultural industries in the general public budget expenditure. It is important to note that due to the data available, expenditures on sports industry could not be excluded, which may slightly impact the results; Per Capita Gross Regional Product and Per Capita Disposable Income reflect the economic development and affluence levels of each province, calculated in Chinese Yuan based on the 2019 currency value; Percentage of persons with tertiary education or above represents the education level of residents in each province.

These five independent variables, along with the TE scores from the Global SBM model as the dependent variable, were input into SPSSAU software to construct the Tobit regression model. The left and right truncation intervals of the dependent variable were set to (0, 1.001), with all 186 samples from 31 provinces during 2014–2019 participating in the model construction. The likelihood ratio test results of the model are shown in Table 7. Here, a p-value less than 0.05 indicates the rejection of the null hypothesis in the Tobit model, signifying that at least one independent variable has a significant impact on the dependent variable. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are used to assess the model's fit and complexity, respectively. Generally, lower values of AIC and BIC are preferable; in this study, both metrics showed relatively small negative values, indicating effective model validity.

Table 7. Likelihood Ratio Tests for the Tobit Model with TE Score as the Dependent Variable.

	−2 Log-Likelihood Value	**Chi-Square Value**	***df***	***p***	**AIC**	**BIC**
Intercept Only	15.597					
Final Model	−97.964	113.561	5	0.000	−85.964	−66.610

The results of the Tobit model are presented in Table 8.

Table 8. Tobit regression model of social benefit impact factors in the cultural industries.

	Regression Coefficient
Distance	0.807 ** (6.225)
Proportion of Urban Population	−0.002 (−0.737)
Degree of financial support	0.081 * (2.324)
Per Capita Gross Regional Product	−0.000 * (−2.159)
Per Capita Disposable Income	−0.000 ** (−3.842)
Percentage of persons with tertiary education or above	0.019 ** (4.728)
Log (Sigma)	−1.682 ** (−32.447)
Likelihood Ratio Rest	χ^2 (5) = 113.561, p = 0.000
McFadden R^2	7.281
Dependent Variable: TE	

* $p < 0.05$, ** $p < 0.01$, z-values in parentheses.

From Table 8, it is observed that among the five independent variables, the z-value for the "Proportion of Urban Population" is −0.737 with a p-value of 0.461, which is greater than 0.05. This indicates that this variable does not exhibit significance and does not impact the TE.

The variable "Degree of Financial Support" has a z-value of 2.324 with a p-value of 0.020, which is less than 0.05, and a regression coefficient of 0.081. This indicates that the variable is statistically significant at the 0.05 level and has a significant positive effect on TE.

The "Per Capita Gross Regional Product" variable has a z-value of −2.159, with a p-value of 0.031, less than 0.05, and a regression coefficient of −0.000. This shows that the variable is significant at the 0.05 level and has a significant negative impact on TE.

The variable "Per Capita Disposable Income" has a z-value of −3.842, with a p-value of 0.000, which is less than 0.01, and a regression coefficient of −0.000. This indicates that the variable is significant at the 0.01 level and negatively affects TE significantly.

The "Percentage of Persons with Tertiary Education or Above" has a z-value of 4.728, with a p-value of 0.000, less than 0.01, and a regression coefficient of 0.019. This shows that the variable is significant at the 0.01 level and positively impacts TE.

In summary, the variables "Degree of Financial Support" and "Percentage of Persons with Tertiary Education or Above" have a significant positive effect on TE, whereas "Per Capita Gross Regional Product" and "Per Capita Disposable Income" have a significant negative effect. The "Proportion of Urban Population" does not influence TE.

The Tobit model from Table 8 is plotted as a more intuitive forest diagram in Figure 2.

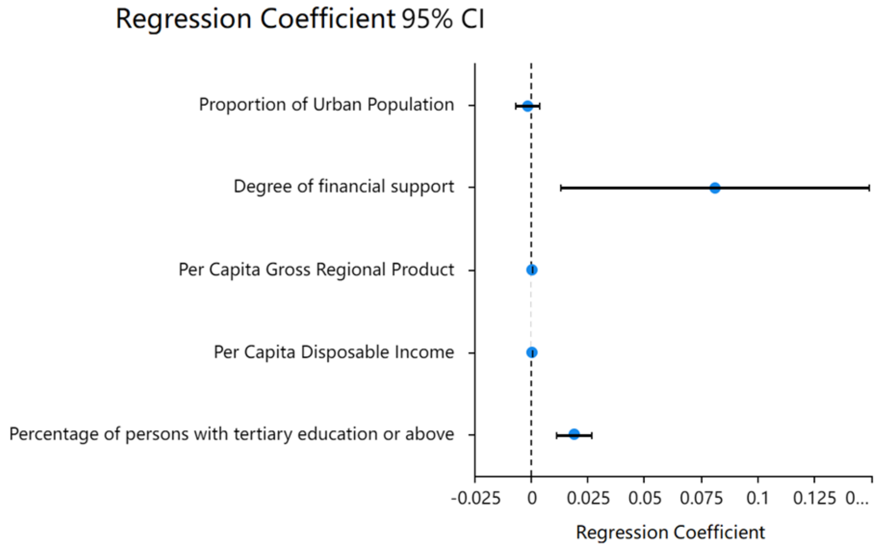

Figure 2. Forest plot of the Tobit model with TE as the dependent variable.

Additionally, this paper constructs a Tobit model with the dependent variable replaced by efficiency scores calculated under the assumption of VRS, allowing for comparative analysis with previous models. The results of the likelihood ratio test for the Tobit model with PTE as the dependent variable are displayed in Table 9. The −2 log-likelihood value, AIC, and Bayesian Information Criterion BIC are all lower than those for the Tobit model using TE as the dependent variable, indicating the superior fit of the model. However, the Chi-square value is comparatively lower, suggesting that the relationship between the dependent and independent variables is less significant than in the Tobit model with TE as the dependent variable.

Table 9. Likelihood Ratio Tests for the Tobit Model with PTE Score as the Dependent Variable.

	−2 Log-Likelihood Value	Chi-Square Value	*df*	*p*	AIC	BIC
Intercept Only	−124.629					
Final Model	−198.803	74.173	5	0.000	−186.803	−167.448

The results of the Tobit model with PTE as the dependent variable are shown in Table 10.

Table 10. Results of the Tobit model with PTE as the dependent variable.

	Regression Coefficient
Distance	0.970 ** (9.804)
Proportion of Urban Population	−0.009 ** (−4.507)
Degree of financial support	0.093 ** (3.504)
Per Capita Gross Regional Product	−0.000 ** (−3.128)
Per Capita Disposable Income	0.000 ** (2.887)

Table 10. *Cont.*

	Regression Coefficient
Percentage of persons with tertiary education or above	0.009 ** (2.962)
Log (Sigma)	−1.953 ** (−37.675)
Likelihood Ratio Rest	χ^2 (5) = 74.173, p = 0.000
McFadden R^2	−0.595
Dependent Variable: PTE	

** $p < 0.01$, z-values in parentheses.

From Table 10, among the five independent variables, the "Proportion of Urban Population" exhibits a z-value of −4.507 with a p-value of 0.000, which is less than 0.01, and a regression coefficient of −0.009. This indicates that the variable is statistically significant at the 0.01 level and has a significant negative effect on PTE.

The variable "Degree of Financial Support" has a z-value of 3.504, with a p-value of 0.000, less than 0.01, and a regression coefficient of 0.093. This shows that the variable is significant at the 0.01 level and positively influences PTE.

The "Per Capita Gross Regional Product" has a z-value of −3.128, with a p-value of 0.002, less than 0.01, and a regression coefficient of −0.000. This indicates that the variable is significant at the 0.01 level and has a significant negative impact on PTE.

The variable "Per Capita Disposable Income" has a z-value of 2.887, with a p-value of 0.004, less than 0.01, and a regression coefficient of 0.000. This demonstrates that the variable is significant at the 0.01 level and has a significant positive effect on PTE.

The "Percentage of Persons with Tertiary Education or Above" has a z-value of 2.962, with a p-value of 0.003, less than 0.01, and a regression coefficient of 0.009. This shows that the variable is significant at the 0.01 level and positively impacts PTE.

Convert Table 10 into the more visually intuitive Figure 3. As illustrated in Figure 3, in the Tobit model with PTE as the dependent variable, three variables—"Degree of Financial Support", "Per Capita Disposable Income", and "Percentage of Persons with Tertiary Education or Above"—significantly positively influence the outcome. Meanwhile, "Proportion of Urban Population" and "Per Capita Gross Regional Product" each significantly negatively impact the results.

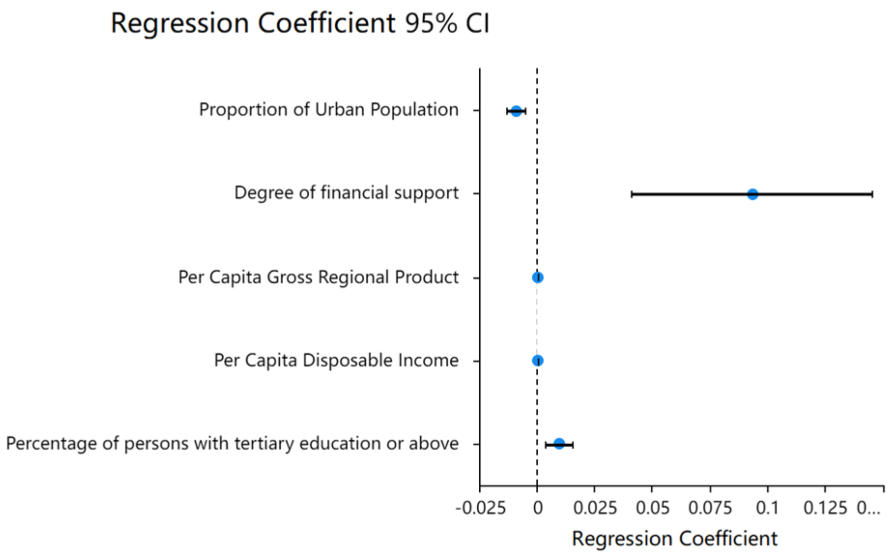

Figure 3. Forest plot of the Tobit model with PTE as the dependent variable.

4. Discussion

4.1. Declining Scale Efficiency in China's Cultural Industries

Figure 4 illustrates data from Table 6, revealing trends in the efficiency scores of China's cultural industries' social benefit model across 31 provinces from 2014 to 2019. As shown in Figure 4, the average TE scores, represented by blue bars, remain relatively stable during this period. In contrast, the average PTE scores, depicted by red bars, generally show an upward trend over the years. Simultaneously, the SE scores, indicated by green bars, demonstrate a gradual decline. This suggests that while the overall TE scores have been maintained, they increasingly rely on improvements in pure technical efficiency, indicative of advancements in technology and management levels within the cultural industries. However, efficiency gains due to the scale of inputs seem to be diminishing over time. This trend is further corroborated in Figure 4, which shows that 24–26 provinces annually experience diminishing returns to scale, constituting the majority of the 31 provinces studied.

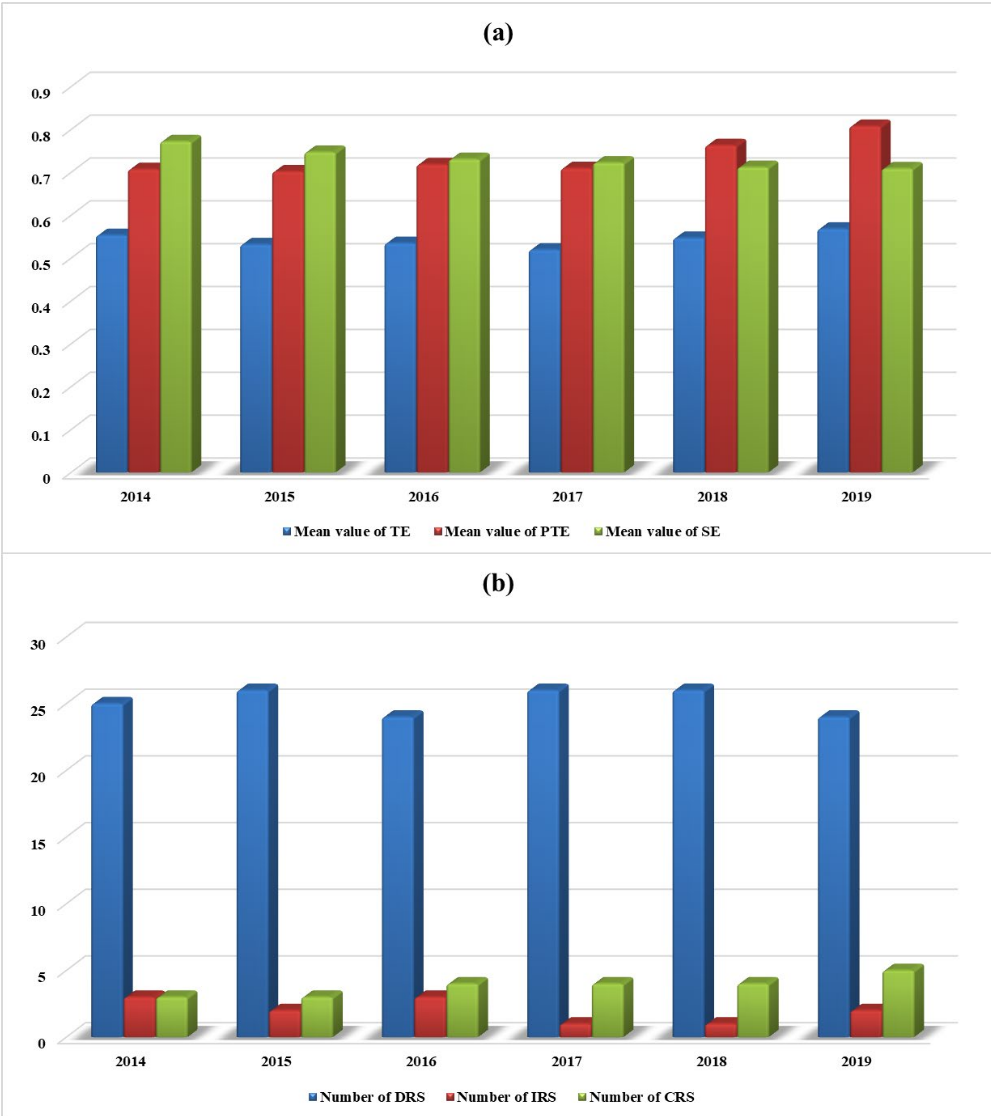

Figure 4. Summary of the Global SBM model for social benefits of the cultural industries in China, 2014–2019. (**a**) 2014–2019 Overview of Global SBM Model Efficiency Scores for Social Benefits in the Cultural Industry Across China's 31 Provinces and Cities; (**b**) Scale of Returns in the Cultural Industry Across the 31 Provinces and Cities.

From the social benefit model of China's cultural industries, it can be observed that the increase in asset investment and revenue generation is no longer as effective in enhancing social impact as before. However, the improvements in management and technological proficiency have led to an enhancement in pure technical efficiency, compensating for the shortcomings in scale efficiency. These characteristics closely resemble the economic models of some relatively mature industries characterized by diminishing marginal returns. Specifically, the decline in scale efficiency suggests that the industry is entering a mature phase, with the enhancement of technical efficiency becoming the core driver of efficiency improvement, as evidenced by studies such as Basu and Fernald [33] on typical American industries entering a state of constant or decreasing returns to scale. Additionally, Potter and Watts [34] found in their research on agglomeration economics that even in the later stages of an industry's lifecycle, including Marshallian agglomeration, a decline in industry performance and diminishing returns can occur. Similarly, Shan, Li et al. [35] discovered in their study of e-commerce in China that the sector has reached a stage where scale efficiency contributes less, with pure technical efficiency emerging as the key driver.

It is crucial to note that this study constructs a social benefits efficiency model for the cultural industries. In this model, the input variables include the annual revenue of the entire cultural industries, which is typically considered a primary output indicator in common economic efficiency models, where higher values indicate higher efficiency scores. Contrarily, in our social benefits model, the output variables include the number of employees, average wages, and taxes—typically considered input variables in economic efficiency models, where smaller values indicate higher efficiency. Thus, the decline in the scale efficiency of social benefits could inversely indicate an increase in the scale efficiency of economic benefits.

Figure 5 depicts the mean scale efficiency values of the social benefits model for China's cultural industries from 2014 to 2019 mapped onto a map of China. Black indicates provinces with the highest scale efficiency, predominantly in the economically less developed regions of Northeast and Northwest China. In contrast, the economically more developed provinces along the southeast coast generally exhibit lower scale efficiency, as indicated by lighter colors. This observation partially corroborates that the scale efficiency of social benefits in the cultural industries may display trends opposite to those in economic efficiency.

Reviewing other recent research findings according to the principles mentioned, Shan et al. [36] demonstrated that the economic scale of China's cultural industries has grown more than the increase in the Gross Domestic Product (GDP) during the same period. In a critical review of China's cultural industries, Xu et al. [37] confirmed the overall trend of economic efficiency growth within the sector. Additionally, Zeng et al. [4] noted that scaling up is key to enhancing the economic efficiency of China's cultural industries. These studies affirm the growth of scale efficiency in the economic performance of the cultural industries and indirectly suggest that the scale efficiency in the social benefits of China's cultural industries is currently on a declining trend.

This presents policymakers with a dilemma: economically, there is an incentive to expand the scale of the cultural industries; however, from a social benefit perspective, increasing the scale does not necessarily enhance the efficiency of the cultural industries' social benefits. It is important to note that this paper assesses the social benefits of the cultural industries using an efficiency evaluation approach. A limitation of this method is that it overly emphasizes "efficiency" while neglecting the "absolute value" of the output. From the perspective of public welfare, the "absolute value" of output is also crucial. In the context of this study, it can be argued that even if the social scale efficiency of the cultural industries is declining and the scale of returns is decreasing, they are still worthwhile if they can provide more job opportunities and better employee benefits. How to adjust empirical analysis methods to better assess the social benefits of industries will be addressed in subsequent research.

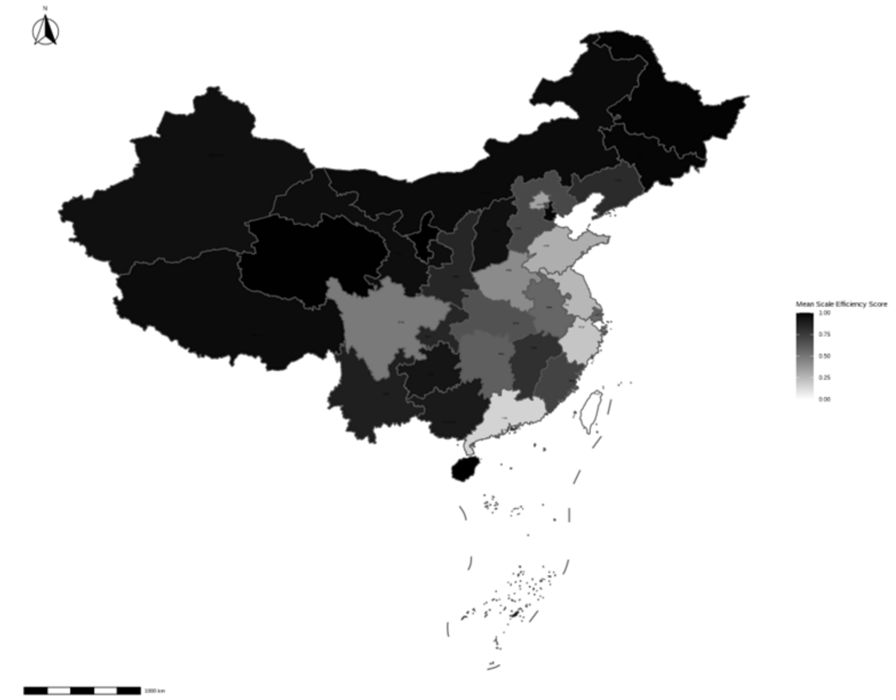

Figure 5. Geographical distribution of scale efficiency scores in China's cultural industries social benefits model.

4.2. The Potential Improvement in Output Quality of Social Benefits in China's Cultural Industries

It is crucial to emphasize that this study focuses on the social benefits of the cultural industries and cannot be simplified by applying the standard that higher economic efficiency implies better outcomes, as is often the case in economic evaluations. As outlined in the Introduction section of this paper, the ultimate goal of enhancing social benefits is not merely to create more economic wealth but to increase societal impact. Assessing social impact is significantly more challenging than the profit-oriented evaluations centered around revenue and profits.

After aggregating and standardizing the data of 31 provinces and 13 output variables for different years, trends in the variations in these output variables over time are depicted in Figure 6.

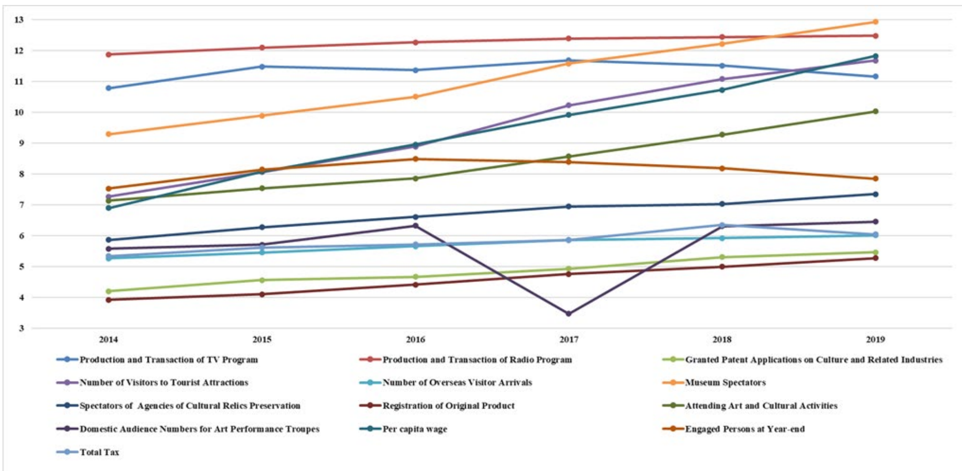

Figure 6. Summary of industry variables for the social benefits model of China's cultural industries, 2014–2019.

From Figure 6, it is evident that the 13 output variables, in general, exhibit an upward trend. For ease of observation, the seven variables with the fastest increasing trends are selected to form Figure 7. As depicted in the figure, these seven variables include Granted Patent Applications on cultural industries, Number of Visitors to Tourist Attractions, Number of Overseas Visitor Arrivals, Museum Spectators, Spectators of Agencies of Cultural Relics Preservation, Registration of Original Product, Attending Art and Cultural Activities, Domestic Audience Numbers for Art Performance Troupes, and Per capita wage.

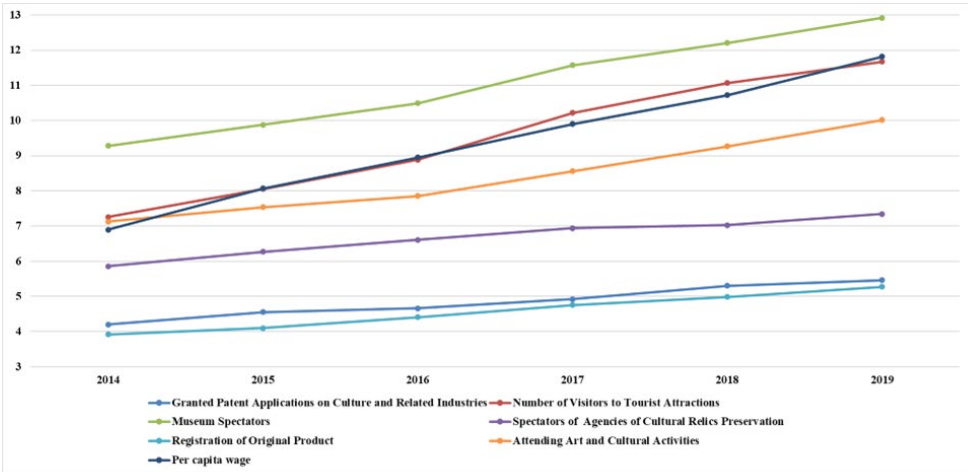

Figure 7. Summary of the fastest-rising industrial variables for the social benefits model of China's cultural industries, 2014–2019.

The rapid upward trend of these output variables, indicating improvements in the treatment of employees in the cultural industries and an increase in audience numbers, seemingly suggests an enhancement in the output quality of social benefits within China's cultural industries. Regrettably, this aspect is not reflected in the DEA model scores. The use of the DEA method, although advantageous due to its adaptability and flexibility in not requiring set weights, also results in certain biases in the final efficiency scores, particularly when applied to evaluations beyond economic efficiency models. Future research will focus on pre-processing data by collecting relevant weights based on the characteristics of the industry and the impact of social benefit outputs.

4.3. Study on the Influencing Factors of Social Benefit Efficiency in Cultural Industries under Constant Returns to Scale

As depicted in Figure 2 and Table 8, "Degree of Financial Support" and "Percentage of Persons with Tertiary Education or Above" have a significant positive impact on the TE scores. In socialist public ownership states like China, financial support often directly corresponds to a critical source of revenue. For instance, the 2021 departmental revenue of China Central Radio and Television Station is reported to be 15,110.616 million yuan, of which 15,096.816 million yuan comes directly from the general public budget expenditures of the Chinese government, with only 138 million yuan from other incomes [38]. Additionally, key resources related to the cultural industries, such as most major museums and tourist attractions, are predominantly state-owned. Therefore, whether assessing the economic or social efficiency of the cultural industries, government financial support plays a crucial role.

The Percentage of Persons with Tertiary Education or Above represents the educational level across the 31 provinces. Higher education often correlates with higher income, a relationship that Jacob Mincer established in 1958 with the creation of the Mincer Earnings Function [39]. Consequently, higher education and income levels typically imply more opportunities for travel, attending cultural and artistic performances, and so forth, all of which contribute significantly to the social benefits of local cultural industries.

Figure 2 also reveals that Per Capita Gross Regional Product and Per Capita Disposable Income significantly negatively impact the TE efficiency scores. These variables represent the level of wealth in a region, and their negative impact on efficiency scores might seem contradictory at first glance. However, it is crucial to note that this paper's focus is on assessing the efficiency of social benefits in the cultural industries. In this context, the revenue of the cultural industries is treated as an input variable, where a smaller size correlates with a higher efficiency score. Consequently, variables representing a region's wealth negatively affect the efficiency scores of the social benefits model. This finding suggests that even in socialist China, where public ownership is predominant, enhancing the efficiency of social benefits in the cultural industries should firstly consider how to more effectively transform economic benefits (such as total industrial output) into social benefits, which include increased employment and a wider impact on people, as outlined in the DEA model constructed for this study.

4.4. Study on Factors Influencing the Social and Economic Benefits of the Cultural Industries under Variable Returns to Scale

As shown in Table 10 and Figure 3, Degree of Financial Support and Percentage of Persons with Tertiary Education or Above continue to exert a significant positive impact on the PTE efficiency score. Additionally, Per Capita Disposable Income also has a notable negative influence. The PTE efficiency score, which is the efficiency score under VRS, represents the pure technical efficiency after excluding the influence of scale efficiency. This encompasses aspects such as sales level, management quality, technological innovation, and financing capabilities. Per Capita Disposable Income indicates the wealth level of residents in each province, with wealthier regions having stronger consumption capabilities in tourism and culture. Once the impact of scale efficiency is removed, this leads to greater outputs in the economic efficiency model of the cultural industries, thus enhancing the efficiency score. Numerous scholars have affirmed the positive impact of increased income on the willingness to travel [40,41]. Some researchers argue that the level of affluence significantly affects the level of cultural consumption [42,43].

Proportion of Urban Population and Per Capita Gross Regional Product exhibit a significant negative impact on the PTE scores. Proportion of Urban Population represents the degree of urbanization in each province. The negative impact of urbanization on cultural industries contradicts some previous studies. For instance, Lorenzen and Frederiksen's research [44] suggests that urbanization brings diversity to cultural industries, as cultural products like films predominantly originate in urban areas. However, these studies often focus on the economic benefits of the cultural industries, while the present study focuses on the efficiency of social benefits within the cultural industries, using indicators that are often the opposite of economic efficiency, possibly leading to opposite results.

Moreover, due to China's strict household registration system, the process of urbanization in China often involves reclassifying large rural administrative areas directly as urban, as Ni et al. [45] found in their study of urbanization in Jiangsu Province. This practice can lead to serious governance dispersion and necessitates ongoing, reflective research. Fang et al. [46] also found that the integration of cultural tourism industries has a significant positive impact on rural revitalization but no significant impact on new urbanization. Conversely, new urbanization can obscure the impact of integration in the cultural tourism industry.

The significant negative impact of Per Capita Gross Regional Product on PTE can be attributed to similar reasons as those affecting TE. In the social benefit efficiency model of the cultural industries, where revenue is a key input variable, Per Capita Gross Regional Product, therefore, has a significant negative impact on PTE.

5. Conclusions

1. In the realm of China's cultural industries, the efficiency of social benefits is currently experiencing diminishing returns to scale, that is, greater asset investment and an-

nual revenue no longer yield proportional increases in tax revenues, employment opportunities, cultural industries outputs, and service coverage. However, this does not necessarily imply that the expansion of industrial scale should be halted. This paper discusses how scaling up could enhance the economic efficiency of the cultural industries while also increasing the absolute output of social benefits. Therefore, the recommendation is to cautiously expand the scale in the future.

2. As evidenced in Section 4.2 and other parts, the efficiency of China's cultural social benefits, supported by pure technical efficiency, remains at a certain level. This reflects recent adjustments in the structure, technological innovations, and management improvements of the cultural industries which have started to positively impact social benefits and have achieved some success. This paper suggests that future policy focus should be on how to further enhance the pure technical efficiency of the cultural industries' social benefits to address potential issues arising from changes in scale. If policymakers continue to emphasize the primacy of social over economic benefits in the cultural industries, then, policy formulation should concentrate on how to more efficiently convert economic benefits into social benefits.
3. Increased financial support and improved education levels can significantly enhance the efficiency of social benefits in the cultural industries. However, China's urbanization process negatively impacts the efficiency of social benefits in the cultural industries under variable returns to scale and should be given special attention. Since the efficiency of social benefits in the cultural industries will require efforts beyond just input scaling in the near future, attention should be paid to how structural adjustments in the cultural industries can adapt to the urbanization process, and it should not solely focus on economic calculations.
4. The output analysis of the social benefits of the cultural industries suggests that the quality of outputs is improving, but there is a lack of further empirical research to substantiate this. China's cultural industries cover a very broad scope, and studying their social benefits involves multiple outputs. While the DEA model's advantage is that it does not require predefined weights for inputs and outputs, this could also be a limitation. Future studies should consider pre-assigning weights to data based on industry experts' opinions, which may better reflect improvements in the quality of cultural industries' outputs.
5. In studies of cultural industries and other vital sectors of the national economy, the relationship between economic and social benefits is delicately balanced, with some aspects aligning and others conflicting. Future research can compare the economic and social benefits of industries to identify their interrelations, which could provide more substantial assistance in policy formulation.
6. Due to limitations related to data sources or data availability, the findings of this study may not fully represent the actual scenario of the cultural industries. Readers are advised to interpret the results with caution. Additionally, future research should aim to obtain more comprehensive or updated data to more accurately assess the social and economic impacts of cultural industries. While this study represents the best effort under the current data conditions, a more complete understanding of the cultural industries still relies on broader data support and in-depth analysis.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16104194/s1, Table S1. Input-Output Variables for the Social Benefit Model of Cultural Industries in 31 Provinces of China, 2014–2019; Table S2. Global SBM Model for the Social Benefit of Cultural Industries in 31 Provinces of China, 2014–2019.

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