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Measuring Efficiency of Public Higher Education Using DEA Model for Sichuan in China

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Abstract: This study uses Data Envelopment Analysis (DEA) and the Malmquist method to investigate efficiency in Sichuan Province's public undergraduate universities by employing a dynamic unbalanced panel data approach and Refining input-output indicators through the application of the Factorial Component Analysis (FCA) method. We find average comprehensive efficiency (0.6601), pure technical efficiency (0.8562), scale efficiency (0.7723), and total factor productivity progress (0.932) for 27 institutions from 2018 to 2022. Despite the increased investment, efficiency gains are modest. Hierarchical correlation with input-output efficiency is noted, and total factor productivity shows an upward trend influenced by financial resources and economies of scale. These findings provide insights for university administrators and policymakers to address inefficiencies and optimize education resources for sustainable development.
Keywords: University Teachers, Innovation Ability, Efficiency Analysis, Education Resources, China Higher Education.

1. INTRODUCTION

As of December 2022, the number of regular universities in China has reached 2,760, marking the transition of Chinese higher education from an elite-oriented stage to a progressively more accessible and widespread phase. Throughout this developmental process, achieving a balance between quantity and quality has become particularly crucial (ChenBin, 2022). Located in the southwestern part of China, Sichuan Province hosts 134 higher education institutions, among which there are 27 public undergraduate universities. The gross enrollment rate in higher education is 51.9%, with a total enrollment of 2.7614 million students, including 990,100 regular undergraduates. Public undergraduate universities play a pivotal role in Sichuan's higher education landscape. The selected research methodology in this study is Data Envelopment Analysis (DEA), which is widely acknowledged as the most reliable approach for studying industries with multiple inputs and outputs, such as higher education, and lacking market price data (Thanassoulis et al., 2016). Given the distinctive classification of China's higher education system, the focus is placed on the efficiency measurement of provincially administered public universities. Leveraging the characteristic of delayed educational input effects (Hanushek & Woessmann, 2020), a framework for input-output indicators is constructed for public undergraduate universities in Sichuan Province, utilizing unbalanced panel data with a one-year lag in output (Khan et al., 2022; Li et al., 2018). The indicator selection in this paper adheres to the educational vision of local governments, resulting in the acquisition of 945 data sets. Z-score and min-max standardization techniques are employed for data normalization, followed by Principal Component Analysis (PCA) for dimensionality reduction. Ultimately, 540 data sets across four categories are determined. The DEA-BCC model is employed for cross-sectional data measurement, and the Malmquist index is used to measure temporal efficiency progress over five years for 27 universities in Sichuan Province. This yields efficiency scores and efficiency progress scores for the 27 provincially administered public undergraduate universities. By unveiling the intricate long-term relationship between educational input and output, this study offers data-supported insights for local higher education's high-quality development and policy formulation.

2. LITERATURE REVIEW

In classical economic research, "how individuals maximize their desires under the constraints of scarce resources" has been regarded as the core and essence (Zhang, 2009). The drive toward "no waste of resources" has propelled the study of production and allocation efficiency, forming the primary theoretical framework of neoclassical economics (Bin, 2020). The Data Envelopment Analysis (DEA) model, first introduced by Charnes, Cooper, and Rhodes in 1978, offers a computational method to assess the effectiveness between decision-making units (DMUs) (Charnes et al., 1978). The fundamental approach involves collecting indicator data for each DMU, calculating its comprehensive technical efficiency, pure technical efficiency, and scale efficiency values to gauge whether the DMU achieves DEA effectiveness. Traditional DEA models conduct static analysis and fail to capture trends and patterns in the changes in DMU-related efficiency. Therefore, by employing time-series data of DMUs (e.g., consecutive years, quarters, months, or weeks), dynamic analysis can reveal efficiency change patterns and reasons, providing additional insights for effective decision-making.

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The Malmquist index, as a model measuring total factor productivity from a dynamic perspective, offers a valuable complement to traditional DEA models, which mainly examine single-factor productivity from a static view (Andersen & Petersen, 1993; Banker et al., 1984; Banker & Thrall, 1992; Elsayed & Khalil, 2017; Yang et al., 2013).

Scholars have widely applied various DEA models to measure higher education efficiency more effectively, including traditional and modified models. Salas-Velasco used the CCR model to assess the internal efficiency of teaching and research in 45 public universities in Spain (Salas-Velasco, 2020). Agasisti et al. combined DEA with the Multiple Criteria Evaluation (MCE) model to evaluate educational efficiency in 12 EU countries (Agasisti et al., 2019). Refer to the summary literature for a more comprehensive review (Pham Van et al., 2022). Due to data acquisition challenges, existing studies predominantly focus on national and provincial panel data. Considering educational input variations, research on internal differentials within local universities still needs to be conducted. This study addresses this gap.In selecting input-output indicators, existing research emphasizes the following aspects of input indicators: human resources inputs, including faculty numbers (Lee & Johnes, 2022; Liang et al., 2021), research personnel numbers (Ghimire et al., 2021; Mammadov & Aypay, 2020), full-time teacher numbers, and the proportion of professors with doctoral degrees (Cossani et al., 2022; Navas et al., 2020); financial resource inputs, including total revenue, government funding (Cossani et al., 2022; Ding et al., 2023), expenditure (Ghimire et al., 2021; Stumbrienė et al., 2022; Sun et al., 2023; Tavares et al., 2021), teaching investment (Chen et al., 2021; Torres-Samuel et al., 2020), and research investment (Torres-Samuel et al., 2020); and stock resource status, such as fixed assets (Chen et al., 2021), research equipment numbers, and infrastructure area (Cossani et al., 2022). Output indicators primarily focus on talent cultivation efficiency, including the number of graduates (Mammadov & Aypay, 2020; Navas et al., 2020; Stumbrienė et al., 2022; Tavares et al., 2021), the number of undergraduate students (Chen et al., 2021), and the number of postgraduate students (Chen et al., 2021; Sun et al., 2023); scientific research achievements, such as the number of publications (Cossani et al., 2022; Ding et al., 2023; Ghimire et al., 2021; Mammadov & Aypay, 2020; Navas et al., 2020), research funding (Chen et al., 2021; Ding et al., 2023; Ghimire et al., 2021; Mammadov & Aypay, 2020), and the quantity of research outcomes (Cossani et al., 2022; Tavares et al., 2021); and societal service, such as technology transfer (Torres-Samuel et al., 2020) and the number of patents (Sun et al., 2023). In recent years, the Principal Component Analysis (PCA) method has been used in DEA measurement to generate input-output indicators more objectively, significantly reducing the subjectivity of indicator selection. (Deng et al., 2022; Xia et al., 2021).

This study focuses on the relatively homogeneous provincially administered public undergraduate universities in Sichuan Province, addressing limitations in existing research. Utilizing the PCA-DEA and Malmquist index, the methodology ensures the reliability of indicators' scientific validity and measurement results.

3. METHOD

This study constructs a comprehensive input-output indicator system for provincially administered public undergraduate universities in Sichuan Province from 2018 to 2022. After standardizing and dimensionality reduction of the data, the study employs the DEA-BCC model for cross-sectional efficiency measurement and the Malmquist index for temporal panel data measurement. By showcasing the efficiency status of 27 provincially administered public undergraduate universities in Sichuan Province, this research offers valuable decision support for developing local higher education. Using z-score and min-max data standardization methods and PCA dimensionality reduction enhances the reliability of indicator selection, while the dual-dimensional measurement of cross-sectional data and panel data results in more accurate conclusions.

Step First: Construct the Evaluation Indicator Framework. A thorough evaluation indicator framework is created in accordance with the concepts of comparability, relevance, efficiency, and adaptability. This approach incorporates commonly used input and output indicators found through careful literature research. There is also mention of the "14th Five-Year Plan for Education Development in Sichuan Province."[1] Formulated in 2022, aligning with the educational development vision and goals set for Sichuan Province between 2021 and 2025. This preliminary stage involves the establishment of an input-output indicator framework.

[1] The higher education development vision outlined in the "14th Five-Year Plan for Education Development in Sichuan Province" encompasses the following key aspects: （1）Promotion of Education Accessibility: Raise the gross enrollment rate of higher education from 51.9% in 2020 to 58.5%； Increase the enrollment scale of regular undergraduate students from 990,100 in 2020 to 1,025,200； Expand the scale of enrolled graduate students from 144,700 in 2020 to 162,900.（2）Enhancement of Education Quality: Implement the Progressive Cultivation Program for First-Class Undergraduate Majors, aiming to establish 500 provincial-level first-class undergraduate majors, with an ambition for approximately 400 majors to achieve national-level first-class status； Develop 3,200 provincial-level first-class undergraduate courses, striving to attain around 400 courses at the national level.（3）Stimulation of Innovative Development: Achieve a "triple growth" target in terms of the total amount of research funding, the quantity of research outputs, and the number of technological achievements converted from research, surpassing the achievements of the end of the 13th Five-Year Plan period；Execute key platform construction projects at the provincial and ministerial levels, with a focus on nurturing and constructing 20 provincial (technological) research centers and 10 national and provincial key laboratories for defense science and technology. Strive to accumulate over 100,000 breakthroughs in cumulative university-industry-research cooperation projects.

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Table 1. Input-Output Indicators

Input Variables	Indicator Code	Indicator Name	Output Variables	Indicator Code	Indicator Name
Education Input	X1	Faculty and Staff Count	Education Output	Y1	Number of Undergraduate Students
	X2	Accumulated Fixed Assets (RMB 10,000)		Y2	Number of Key Provincial Disciplines
	X3	Budgeted Revenue (RMB 10,000)		Y3	Amount of Technology Transfer (RMB 10,000)
				Y4	Number of High-Level Published Papers

Step Two: Sample Selection. By adopting a full-sample investigation strategy, this research aims to encompass all relevant public undergraduate universities within the scope of analysis. This approach ensures a comprehensive representation of the target universities, providing a more holistic understanding of the efficiency assessment and contributing to the robustness of the study’s findings. The sample and corresponding coding rules are outlined in Table 2.

Table 2. Public Undergraduate Universities in Sichuan Provincial

DUM	Name of University or College	DUM	Name of University or College
DUM 1	Chengdu University of Technology	DUM15	Yibin University
DUM 2	Xihua University	DUM16	Sichuan University of Arts and Science
DUM 3	Sichuan University of Science & Engineering	DUM17	Panzhihua University
DUM 4	Southwest University of Science and Technology	DUM18	Xichang University
DUM 5	Sichuan Agricultural University	DUM19	Mianyang Teachers’ college
DUM 6	Chengdu University of Traditional Chinese Medicine	DUM20	Neijiang Normal University
DUM 7	Sichuan Normal University	DUM21	Aba Teachers University
DUM 8	China West Normal University	DUM22	Chengdu Normal University
DUM 9	Southwest Petroleum University	DUM23	Chengdu Sport University
DUM 10	Chengdu University of Information Technology	DUM24	Sichuan Police College
DUM 11	Southwest Medical University	DUM25	Sichuan Tourism University
DUM 12	North Sichuan Medical College	DUM26	Chengdu Technological University
DUM 13	Chengdu Medical College	DUM27	Sichuan Conservatory of Music
DUM 14	Leshan Normal University		

Step Third: Data Collection. Following the consensus that education exhibits delayed effects (Hanushek & Woessmann, 2020), this study employs an unbalanced input-output dataset. Data collection for input indicators spans 2017 to 2021, while data for output indicators spans 2018 to 2022. Unbalanced data with a one-year lag between inputs and outputs is used as a set of analytical variables. Data is sourced from various reliable and authoritative educational statistics and reports, including China Education Statistics Yearbook (2017-2021)、Sichuan Province Education Statistics Yearbook (2017-2021). Sichuan Province Education Funding Statistical Reports (2017-2022)、Sichuan Province Education Department’s Budget Reports (2017-2022)、China National Knowledge Infrastructure (CNKI) journal search、Interviews conducted by the Sichuan Provincial Education Department.

Step Fourth: Data Cleaning and PCA Analysis. A data standardization process using z-score and min-max methods is employed based on the raw data. This process transforms all indicators to fall within the range of 0 to 1, achieving both dimensionless quantification and homogenization of the data. The purpose of data standardization is to ensure comparability and consistency among the diverse indicators. Subsequently, the Principal Component Analysis (PCA) method is applied to extract principal components from the initial evaluation indicator framework. PCA helps condense the original indicators’ information into smaller uncorrelated variables while preserving as much variance as possible. The process involves calculating each principal component’s eigenvalues, variance contribution ratios, and cumulative variance contribution ratios. This analysis aids in identifying the most influential components that capture the essential variation within the data.

Step Five: DEA and Malmquist Analysis.Using the cleaned data and the indicators obtained through PCA, the DEAP2.1 software is employed for Data Envelopment Analysis (DEA) and Malmquist analysis.

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4. RESULTS AND DISCUSSION

All indicator values have been scaled to lie within the range of 0 to 1 using a two-step method of z-score and min-max normalization to the raw data, producing dimensionless quantification and homogeneity. The outcomes are displayed below.

Table 3. Descriptive Statistics for Input-Output Variables (2018-2022)

Variable Name	Sample Size	Max	Min	Mean	Std Dev	Median	Variance
X1_z-score_min-max	135	1	0	0.379	0.261	0.338	0.068
X2_z-score_min-max	135	1	0	0.314	0.224	0.24	0.05
X3_z-score_min-max	135	1	0	0.318	0.241	0.235	0.058
Y1_z-score_min-max	135	1	0	0.425	0.274	0.356	0.075
Y2_z-score_min-max	135	1	0	0.262	0.233	0.2	0.054
Y3_z-score_min-max	135	1	0	0.031	0.142	0	0.02
Y4_z-score_min-max	135	1	0	0.265	0.284	0.108	0.081

Data Source: All original data were computed using SPSSPRO and compiled by the authors. Due to space constraints, the presentation of the raw data and the calculated scores for each year is not feasible in this context.

Table 3 shows substantial variability across the numerical ranges of individual indicators and noteworthy disparities between mean and median values, accompanied by relatively high standard deviations. These manifestations imply pronounced heterogeneity among higher education institutions concerning their input and output dynamics. This inter-indicator divergence may signify that certain institutions exhibit commendable resource utilization efficiency while others benefit from enhancement initiatives. The application of DEA analysis serves as an instrumental approach to unearth underlying issues, optimize resource allocation, elevate performance standards, and thereby contribute to the advancement of sustained growth within the entire educational ecosystem.

Table 4. KMO Test And Bartlett's Sphericity Test

KMO value		0.852
Bartlett's sphericity test	Approximate Chi-Square	882.215
	Df	21
	P	0.000***

注：***、**、*respectively represent Significance levels of 1%, 5%, and 10% respectively.

From Table 4, the Kaiser-Meyer-Olkin (KMO) test exhibited a value of 0.852, indicating a commendable measure of data adequacy. Additionally, the results of Bartlett's sphericity test revealed a remarkably significant P-value of 0.000***, signifying a notable significance level. Consequently, the null hypothesis was rejected, underscoring the existence of correlations among the various variables. The validity of the principal component analysis is further underscored by these outcomes, demonstrating an appropriate level of suitability for the conducted analysis.

Table 5. Total Variance Explanation

Component	Eigenvalues	Variance Explained (%)	Cumulative Variance Explained (%)
1	4.676	66.795	66.795
2	0.906	12.946	79.741
3	0.753	10.755	90.496
4	0.315	4.498	94.993
5	0.194	2.773	97.767
6	0.086	1.229	98.996
7	0.07	1.004	100

Table 6. Component Matrix Table

variable	Component			
	1	2	3	4
Y1_z-score_min-max	0.189	-0.317	-0.115	0.988
Y2_z-score_min-max	0.119	0.173	1.081	0.001
Y3_z-score_min-max	0.098	0.94	-0.258	0.466
Y4_z-score_min-max	0.189	0.105	-0.236	-0.948
X1_z-score_min-max	0.198	-0.248	-0.127	0.56
X2_z-score_min-max	0.191	-0.129	-0.091	-0.878
X3_z-score_min-max	0.207	0.006	0.026	0.02

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Tables 5 and 6 show that the cumulative variance explained by the first four principal components reaches 94.993%. This signifies that these initial four principal components have captured a significant portion of the data variability. Therefore, we select the indicators corresponding to these four principal components as the final set of indicators. By choosing indicators most correlated with these principal components, we ensure the capture of the most significant variations within the data. It is noteworthy that some eigenvalues exhibit relatively more minor values. However, in the context of DEA analysis, considering the commonality among variables, a substantial loss of information due to extensive one-dimensional data reduction might introduce bias into empirical result analysis. Hence, considering the unique characteristics of higher education institutions, we choose to retain a subset of data with eigenvalues lower than 1. This approach serves to optimize model performance, ensuring that the analysis of the results remains both reasonable and accurate (Xia et al., 2021). Based on the component matrix table, we subsequently refined our selection and chose X1, X3, Y1, and Y4 as the input-output indicators for the DEA analysis.Using X1, X3, Y1, and Y4 as input-output variables, following an input-oriented approach and considering variable returns to scale in the BCC model, we calculated the efficiency scores for the years 2018 to 2022. The 5-year average efficiency results for the 27 higher education institutions are presented below. A score of 1 signifies that the institution has achieved relative optimal efficiency, while a score below 1 indicates suboptimal efficiency. A lower score corresponds to lower efficiency.

Table 7. BCC Average Efficiency of Public Undergraduate Universities in Sichuan Province (2018-2022)

firm	**crste**	**vrste**	**scale**	**firm**	**crste**	**vrste**	**scale**
DUM1	0.684	1	0.684	DUM15	0.7098	0.9342	0.7522
DUM2	0.6968	1	0.6968	DUM16	0.8252	0.9846	0.8376
DUM3	0.6508	0.983	0.661	DUM17	0.4236	0.4904	0.8378
DUM4	0.62	0.8926	0.7054	DUM18	0.6606	0.84	0.8056
DUM5	0.6432	1	0.6432	DUM19	0.6822	0.8276	0.8222
DUM6	0.8808	1	0.8808	DUM20	0.617	0.8404	0.7662
DUM7	0.5914	0.8868	0.6606	DUM21	1	1	1
DUM8	0.5136	0.7588	0.6982	DUM22	0.8196	0.9196	0.8762
DUM9	0.6634	0.965	0.6846	DUM23	0.3716	0.482	0.782
DUM10	0.6078	0.7834	0.7798	DUM24	0.1794	0.7778	0.2338
DUM11	0.7374	0.84	0.8962	DUM25	1	1	1
DUM12	0.7582	0.8938	0.8326	DUM26	0.7602	0.9248	0.8102
DUM13	0.7578	0.8792	0.8554	DUM27	0.3564	0.4234	0.8358
DUM14	0.6132	0.79	0.8136	Average	0.6601	0.8562	0.7723

Note: crste = technical efficiency from CRS DEA， vrste = technical efficiency from VRS DEA scale = scale efficiency = crste/vrste

Data Source: The standardized data were computed using DEAP2.1 software and compiled by the authors. Due to space constraints, only the 5-year average scores are presented in this context.

From Table 7: In terms of cross-sectional performance, significant variations are observed in the comprehensive efficiency scores of higher education institutions. Only two institutions achieve a comprehensive efficiency score of 1, while the efficiency scores across various institutions display substantial disparities. This suggests the presence of factors such as the underutilization of resources or management issues within public undergraduate institutions in Sichuan. Pure technical efficiency scores exhibit relatively better performance, with 12 institutions surpassing a score of 0.9. However, some institutions need to demonstrate higher pure technical efficiency scores, prompting attention to whether there might be issues related to technological innovation lag or the insufficient utilization of best practices. On the other hand, scale efficiency scores generally fall below the technical efficiency scores, indicating room for improvement in their efficiency at given scales.

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Table 8. Malmquist Average Efficiency of Public Undergraduate Universities in Sichuan Province (2018-2022)

DUM	effch	techch	pech	sech	tfpch	DUM	effch	techch	pech	sech	tfpch
DUM1	1.0524	0.9184	1.0000	1.0524	0.9393	DUM15	0.9101	0.9370	0.9763	0.9237	0.8738
DUM2	1.0368	0.8894	1.0000	1.0368	0.9208	DUM16	1.1280	0.8851	1.0019	1.1152	0.8830
DUM3	1.1196	0.9052	1.0024	1.1001	0.9690	DUM17	1.8148	0.8953	1.3612	1.0871	1.4778
DUM4	1.1036	0.8791	1.0337	1.0832	0.9140	DUM18	0.9808	0.9234	0.8796	1.1097	0.8680
DUM5	1.0021	0.9063	1.0000	1.0021	0.8888	DUM19	1.0533	0.9094	0.9737	1.0708	0.9305
DUM6	1.0840	0.9668	1.0000	1.0840	0.9993	DUM20	0.9804	0.8927	0.8540	1.1582	0.8498
DUM7	1.0440	0.8907	1.0033	1.0403	0.9385	DUM21	1.0000	0.8372	1.0000	1.0000	0.8263
DUM8	1.1447	0.8669	1.0411	1.1126	0.9280	DUM22	1.0961	0.9107	1.0133	1.0728	1.0103
DUM9	1.0626	0.9441	1.0286	1.0367	0.9698	DUM23	0.8723	0.9121	0.8751	1.0499	0.7500
DUM10	1.0677	0.8779	0.9759	1.0951	0.9203	DUM24	0.7832	0.9434	1.0146	0.8375	0.7298
DUM11	1.2027	0.8866	1.1547	1.0543	0.9968	DUM25	1.0000	0.7146	1.0000	1.0000	0.7380
DUM12	1.1722	0.8814	1.0498	1.1126	1.0070	DUM26	1.1828	0.9462	1.0459	1.1323	1.0408
DUM13	1.1286	0.8833	1.0244	1.0774	0.9618	DUM27	1.0270	0.8894	1.0148	1.0071	0.9020
DUM14	1.0658	0.9174	1.0544	1.0996	0.9415	Average	1.0783	0.8966	1.014	1.0574	0.9323

Note: "effect" =comprehensive efficiency progress, "tech" = technological progress, "pech" = pure technical efficiency progress, "sech" = scale efficiency progress, "teach" = total factor productivity progress. "teach" = "tech," × "sech," × "pech."

Data Source: The standardized data were computed using DEAP2.1 software and compiled by the authors. Due to space constraints, only the 5-year average scores are presented in this context.

From Table 8: The Malmquist scores greater than 1 indicate overall efficiency progress, scores less than 1 signify efficiency decline, and scores equal to 1 suggest unchanged efficiency levels. Examining the panel data, it is evident that only four higher education institutions among Sichuan's public undergraduate institutions achieved notable improvements in total factor productivity from 2018-2022. This observation aligns with the recent trends in the development of higher education in Sichuan Province. However, it is worth noting that "DUM3" and "DUM5" experienced a decline in total factor productivity, despite their favorable performance in the cross-sectional data analysis. This suggests that these two institutions performing well in specific years, may not be leading the forefront of higher education development in Sichuan Province.

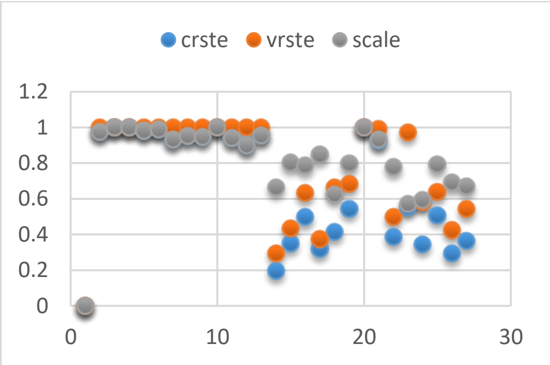

Figure 1. Average Efficiency Distribution Chart (BCC)

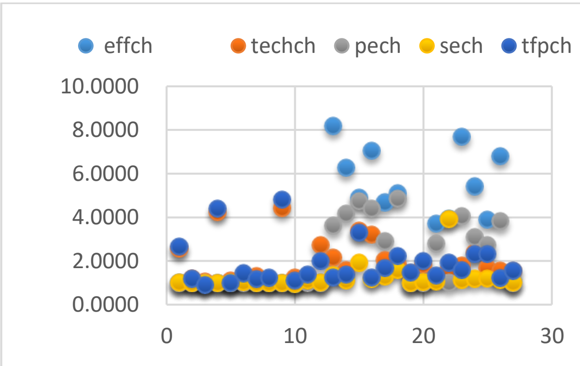

Figure 2. Average Efficiency Distribution Charte (Malmquist)

From Figures 1 and 2: This data reveals the distribution and disparities of static and dynamic efficiency among Sichuan's public undergraduate institutions. Higher education administrators can use these results to focus on improving and enhancing low-efficiency indicators, optimizing the allocation of educational resources, and enhancing overall institutional performance. Furthermore, policymakers can utilize these findings to develop more targeted policies, promoting continuous development and optimization of the entire education system.

An unexpected observation from the analysis of institutions with effective total factor efficiency is that a considerable number of non-capital city institutions outperformed their counterparts in Chengdu. This suggests that some institutions outside the capital city exhibit redundant input without achieving appropriate technological and scale efficiency levels. Therefore, there is significant room for improvement in resource utilization levels and allocation scale.

5. CONCLUSION

This study focuses on 27 public undergraduate institutions in Sichuan Province from 2018 to 2022. the classical DEA-BBC model and the Malmquist index were used to conduct static and dynamic analyses of the higher education efficiency of each institution from 2018 to 2022. Based on the research findings, the following conclusions are drawn:

(1)Over the past five years, Sichuan's provincial undergraduate institutions have consistently increased their input. However, the improvement of infrastructure and the level of financial investment still needs to meet the development needs of the institutions.

(2) The study demonstrates a positive correlation between the tier of Sichuan's provincial undergraduate institutions and the efficiency of educational input and output. This alignment reflects the current emphasis on different-tier institutions in Sichuan Province. The research also reveals that economic development, institutional reputation, and academic discipline types significantly influence the input-output efficiency of different-tier institutions. At the same time, the resource allocation scale has a more significant impact on the development of provincial institutions.

(3) Overall, Sichuan's higher education total factor productivity (TFP) is on an upward trend, with financial resources and economies of scale playing essential roles in educational development. Technological progress efficiency contributes to development, but technical efficiency is constraining it. Therefore, the key to improving TFP lies in enhancing technical efficiency. Over time, the total factor productivity experiences fluctuations, demonstrating a "U"-shaped changing trend.

(4). Historical factors, human resources, and funding support positively impact the comprehensive efficiency of higher education in Sichuan. This underscores that various factors, including political aspects such as government policy support at all levels, social factors like geographic location and institutional reputation, and internal factors like faculty structure and student conditions, influence higher education institutions.

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