ISSN 2616-5902 Vol. 8, Issue 1: 170-176, DOI: 10.25236/AJBM.2026.080123

Operational Efficiency Evaluation of Tourism Listed Firms in China: A Slack-Based Measure DEA Approach

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Abstract: *Enhancing operational efficiency serves as a critical foundation for the high-quality development of China's tourism industry. However, existing studies have shown limited attention to evaluating the operational efficiency at the firm-level. To this end, this study applies the Slack-Based Measure Data Envelopment Analysis (SBM-DEA) method to measure the operational efficiency of 13 tourism listed firms in China from 2017 to 2023. The findings reveal that the overall operational efficiency of tourism firms remains at a low level, suggesting substantial potential for improvement. From the perspective of heterogeneity, firms operating comprehensive cultural tourism perform better than those operating natural scenery tourism, and firms located in the eastern region demonstrate higher efficiency levels than their counterparts in the central and western regions. In addition, the efficiency gap among firms narrows following the pandemic. The input and output improvement analysis reveals a significant excess in employee investment and the deficiency in tourists received. Based on these findings, this study also provides some suggestions for improving operational efficiency.*

Keywords: *Operational efficiency, Tourism firm, SBM model, Input and output improvement*

1. Introduction

Tourism, as a vital sector within the modern service industry, plays an increasingly significant role in the national economy and serves as a major driver of consumption upgrading. According to the World Travel and Tourism Council [1], the tourism sector contributes around 10.9 trillion USD to global GDP, representing 10% of total global economic output. It also supports 357 million jobs globally, which equates to one-tenth of total global employment. Driven by rising consumer demand, the tourism industry continues to expand rapidly, contributes positively to local economic growth, and aids in the preservation of natural scenery and traditional culture [2]. In China, tourism emerges as a crucial pillar in stimulating domestic consumption and promoting regional economic integration, thereby promoting the rapid development of the national service industry [3].

Operational efficiency refers to a firm's capacity to effectively convert inputs into outputs through streamlined and optimized internal processes [4]. In the existing literature, the majority of Data Envelopment Analysis (DEA)-based studies on tourism operational efficiency concentrate on the regional level [6,7]. While these macro-level analyses provide valuable insights, they fail to identify firm-level efficiency variations. This limitation restricts the identification and analysis of firm-specific inefficiency patterns. In contrast to the comprehensive assessments conducted at the industry-level, firm-level efficiency analysis offers a more granular understanding of business management practices, operational processes, and the misalignment between inputs and outputs. Therefore, conducting firm-level operational efficiency analysis in the tourism sector is both necessary and valuable.

To the best of our knowledge, DEA-based efficiency assessments are conducted on tourism listed firms in China and individual theme parks in South Korea [8,9]. Among the limited studies available, Hu is the most directly related to our research, which analyzes productivity dynamics and overall efficiency trends of tourism listed firms in China using longitudinal data spanning from 2014 to 2019 [8]. To address this research gap, this study employs the slack-based measure (SBM) model to evaluate the operational efficiency of Chinese A-share tourism listed firms over the period from 2017 to 2023. This research makes two main contributions. First, unlike previous studies, this research separately analyzes tourism firms primarily engaged in scenic area management and further categorizes them into natural scenery tourism firms and comprehensive cultural tourism firms based on their core operational focus. This detailed classification significantly enhances the accuracy of the efficiency evaluation. Second, this study adopts a dynamic time span from 2017 to 2023, covering the pre-pandemic, pandemic, and post-pandemic periods. This timeframe enables a more comprehensive analysis of the current operating conditions of different types of tourism firms. By analyzing these temporal variations, the study offers empirical evidence that advances theoretical understanding and informs practical responses in the context of post-pandemic recovery.

2. Literature Review

2.1 DEA Method

Originally introduced by Charnes et al. [10], DEA has evolved from radial models (CCR and BCC) to non-radial measures to enhance evaluation accuracy. Although radial models distinguish between technical and scale efficiencies, their reliance on proportional adjustments fails to account for input/output slacks, potentially compromising reliability [11]. Consequently, the Slack-Based Measure (SBM) was proposed to identify non-proportional inefficiencies through direct slack quantification [12]. This advantage makes the SBM model increasingly widely used in the evaluation of enterprise efficiency, and the same applies in the field of tourism [13].

2.2 Efficiency measurement in tourism based on DEA

International The tourism industry is a complex service system that integrates multiple sectors such as travel agencies, accommodation, and leisure [14]. Current literature primarily evaluates tourism efficiency through two dimensions: industry-level and firm-level analyses. Early research focused heavily on the hotel sector due to data availability, revealing that operational efficiency is significantly influenced by geographic location and firm size [15].

At the industry level, extensive studies have utilized DEA and SBM models to identify spatial disparities in tourism efficiency. Research conducted in China [5,16] and Latin America [17] consistently demonstrate that operational efficiency is imbalanced. For instance, Chinese research has found that the operational efficiency of eastern provinces is better than that of western provinces. Despite these findings, firm-level investigations into tourist attractions remain relatively scarce compared to industry-level assessments [9]. While some scholars have examined Chinese listed tourism firms up to 2019 [8], there is a critical lack of updated research covering the 2017–2023 period. This study addresses this research gap by employing the SBM model to evaluate the efficiency of Chinese tourism listed firms.

3. Methodology

3.1 Input and output indicators

In this study, drawing on these prior studies and considering the fundamental operational processes of tourism firms, we choose fixed assets and employees as the input indicators. These two indicators are widely recognized as key drivers of operational activities in the tourism sector. For the output indicators, tourism revenue and tourists received are selected, as they directly reflect the economic performance of the firms. Figure 1 illustrates this process, showing how fixed assets and employees are utilized to generate tourism revenue and tourists received. By using these clearly defined indicators, we provide a reliable and accurate assessment of the operational efficiency of the tourism firm.

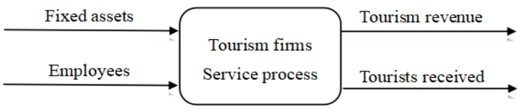

Figure 1. Service process of tourism firms.

3.2 Operational efficiency estimation in SBM-DEA model

To measure the operational efficiency of tourism firms in China, we assume that there exist n decision making units (DMUs), each denoting a firm's operation process (FSj, j=1,..., n). The operation process is modeled as the use of fixed assets (XC) and employees (XL) inputs to generate the outputs of operating tourism revenue (YO) and tourists received (YV). A similar input and output setting has also been applied in some existing tourism studies [5,18]. As a non-radial DEA model, the SBM model effectively identifies sources of inefficiency in the production process by detecting each 'input excess' and 'output shortfall' to determine the maximum slacks [12]. Due to these advantages, the SBM model has been widely applied in the field of tourism efficiency estimation [19]. The operational efficiency evaluation model for tourism firms is constructed as follows.

In model (1), the subscript 0 denotes the evaluated DMU. $ts_l^- = S_l^-, ts_c^- = S_c^-, ts_o^+ = S_o^+, ts_v^+ = S_v^+$ are slack variables, referring to *XL*, *XC*, *YO*, and *YV*. $\lambda t = \eta$ denotes the intensity variable, meaning the participation degree of each DMU in constructing the optimal production frontier. The objective value θ_0^* denotes the overall operational efficiency for the evaluated DMU, ranging from 0 and 1. The evaluated tourism firm would be deemed as efficient if all the optimal slacks are equal to zero; otherwise, it is inefficient. If the operational efficiency score of a tourism firm is higher than those of other firms, this firm performs better than other firms.

$$
\begin{aligned}
&\theta_0 = \min\left(t - \frac{1}{2}\left(\frac{S_l^-}{XL_0} + \frac{S_c^-}{XC_0}\right)\right) && \sum_{j=1}^{n} \eta_j XK_j + S_c^- = tXC_0, && \\
&\text{s.t.} \quad t + \frac{1}{2}\left(\frac{S_o^+}{YO_0} + \frac{S_v^+}{YV_0}\right) = 1 && \sum_{j=1}^{n} \eta_j YO_j - S_o^+ = tYO_0, && \sum_{j=1}^{n} \eta_j = t, \\
&\sum_{j=1}^{n} \eta_j XL_j + S_l^- = tXL_0, && \sum_{j=1}^{n} \eta_j YC_j - S_v^+ = tYV_0, && \eta_j, S_l^-, S_c^-, S_o^+, S_v^+ \geq 0,\ j = 1,2,...,n
\end{aligned}
\tag{1}
$$

4. Empirical Result

4.1 Sample and data source

As of 2025, 22 tourism firms are listed on China's A-share market. Since this study focuses exclusively on tourism firms whose core business involves scenic area management, two firms primarily engaged in hotel management are excluded. To ensure research validity, data on fixed assets, employees, and tourism revenue are collected from the annual reports of the selected firms. Data on tourist reception are obtained from firm annual reports and relevant official websites. Based on data availability for tourist reception, 13 tourism firms are ultimately selected as the research sample.

4.2 Overall analysis of operational efficiency

The operational efficiency (OE) results of the 13 tourism listed firms from 2017 to 2023 are listed in Table 1. The overall mean efficiency is 0.4616, which indicates that many firms operate significantly below their potential and require substantial optimization. The results reveal a high degree of operational efficiency heterogeneity among the sampled firms. Specifically, ZQL and JHLY consistently remained at the production frontier with perfect OE scores of 1.0000, while XYWL also demonstrated strong management practices with an average score of 0.9789. In contrast, several firms exhibited persistent inefficiencies. CBS recorded the lowest average OE of 0.1446, followed by EMSA (0.1998) and HSLY (0.2204). These significant disparities suggest that structural weaknesses and suboptimal resource allocation remain prevalent, highlighting the need for more effective operational strategies across the industry.

Table 1. Operational efficiency of 13 tourism listed firms from 2017 to 2023.

DMU	2017	2018	2019	2020	2021	2022	2023	2017-2023
TMH	0.0653	0.0081	0.0850	0.0989	1.0000	0.3283	0.6652	0.3215
ZQL	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
XYWL	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8524	0.9789
ZJJ	0.2998	0.1478	0.2406	0.1048	0.1000	0.1497	0.6718	0.2449
HSLY	0.2121	0.1533	0.2037	0.1431	0.1444	0.1789	0.5074	0.2204
JHLY	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
CBS	0.0767	0.0451	0.0961	0.0434	0.0582	0.1310	0.5618	0.1446
STSD	0.0928	0.0713	0.2064	0.4712	0.4758	0.2841	1.0000	0.3717
GLLY	0.3148	0.2865	0.3141	0.1148	0.1878	0.1181	0.5573	0.2705
LJGF	0.1255	0.0676	0.2454	0.2702	0.1116	0.2001	0.7037	0.2463
XZLY	0.0841	0.0970	0.2857	0.5169	0.1644	0.3670	1.0000	0.3593
YNLY	0.4931	0.7393	0.6891	0.8096	0.6733	0.4605	0.6293	0.6420
EMSA	0.1272	0.1147	0.1964	0.1234	0.1796	0.1668	0.4903	0.1998
Mean	0.3763	0.3639	0.4279	0.4382	0.4689	0.4142	0.7415	0.4616

ISSN 2616-5902 Vol. 8, Issue 1: 170-176, DOI: 10.25236/AJBM.2026.080123

Figure 2 illustrates the evolving distribution of operational efficiency from 2017 to 2023. In 2017, efficiency scores were predominantly concentrated at lower levels, which indicates widespread underperformance across the industry. Although the median efficiency gradually improved during 2018 and 2019, this upward trend was reversed in 2020 and 2021 because of the pandemic. During this disruption phase, the distribution shifted downward with reduced variance, suggesting a universal decline in operational efficiency. Following a tentative recovery in 2022, the industry experienced a sharp surge in median efficiency in 2023, signaling a robust return to operational effectiveness as firms adapted to new market demands. Despite these overall gains, persistent disparities among firms underscore the necessity for differentiated development strategies. Consequently, systematically classifying tourism firms based on their operational profiles is essential for providing targeted strategic recommendations.

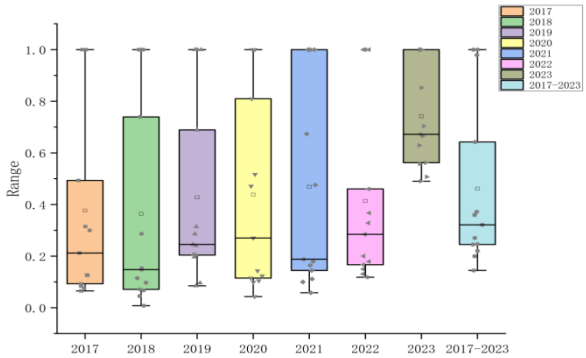

Fig 2. Box plot of tourism operational efficiency distribution.

4.3 Classification analysis

4.3.1 Efficiency analysis from a business perspective

This study conducts a comprehensive analysis of the operational efficiency of 13 tourism listed firms from 2017 to 2023, based on their distinct business models: natural scenery tourism and comprehensive cultural tourism. Firms engaged in natural scenery tourism include ZJJ, GLLY, JHLY, CBS, HSLY, EMSA, and STSD. In contrast, comprehensive cultural tourism firms comprise ZQL, TMH, XYWL, YNLY, XZLY, and LJGF. The comparison results are shown in Figure 3.

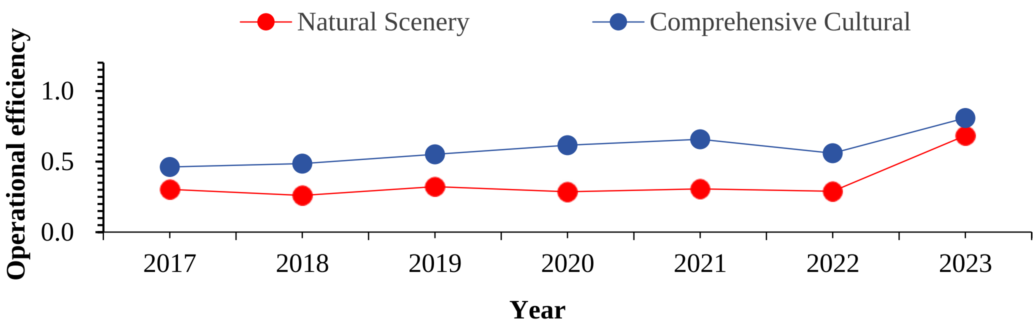

Fig 3. Average operational efficiency of tourism listed firms in natural scenery and comprehensive cultural tourism firms (2017-2023).

Throughout the seven-year period, comprehensive cultural tourism firms maintained a superior OE with a mean value of 0.5913, whereas natural scenery firms recorded a lower average of 0.3503. The two groups exhibited divergent trends during the pre-pandemic and pandemic phases. While natural scenery firms faced declining efficiency due to their sensitivity to external disruptions, cultural tourism firms demonstrated greater resilience by improving their OE scores through diversified business models. In the 2023 recovery phase, both sectors experienced a significant rebound, with natural scenery firms achieving a sharp increase from 0.2898 to 0.6841, driven by surging outdoor tourism demand. Despite this recovery, cultural tourism firms remained at a higher efficiency level of 0.8084. These findings suggest that diversified revenue streams and deeper cultural engagement provide a competitive advantage, enabling firms to adapt more effectively to market shifts and evolving consumer preferences.

ISSN 2616-5902 Vol. 8, Issue 1: 170-176, DOI: 10.25236/AJBM.2026.080123

4.3.2 Efficiency analysis from a region perspective

According to the classification of the National Bureau of Statistics of China, the country is geographically divided into three major regions: eastern, central, and western. Among the 13 tourism firms examined in this study, TMH, ZQL, and XYWL are located in the eastern region. ZJJ, HSLY, JHLY, CBS, and STSD are categorized in the central region. GLLY, LJGF, XZLY, YNLY, and EMSA are situated in the western region. Variations in operational efficiency across the three regions from 2017 to 2023 are illustrated in Figure 4.

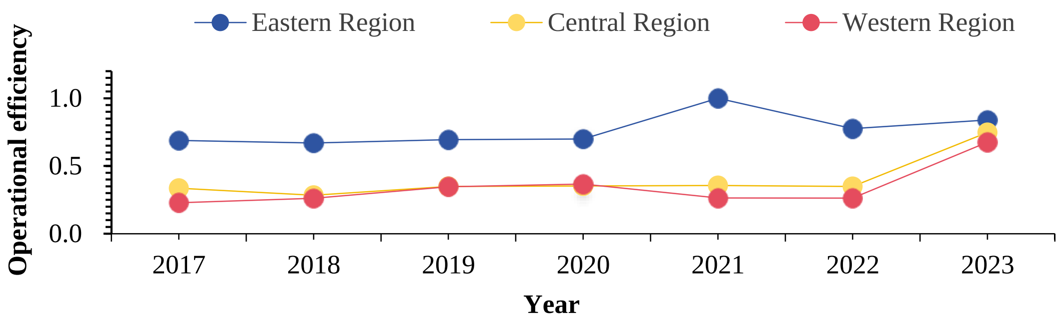

Fig 4. Average operational efficiency of tourism listed firms in Eastern, Central, and Western China (2017-2023).

Throughout the observation period, significant spatial disparities in operational efficiency (OE) were evident among the three regions. The eastern region led with an average score of 0.7668, substantially higher than the central (0.3963) and western (0.3436) regions. During the pre-pandemic phase, the east and central regions experienced slight declines, while the western region showed an initial upward trend. In the pandemic period, the eastern region demonstrated remarkable resilience, as its OE reached the production frontier of 1.000 in 2021. In contrast, the western region suffered a sharp decline due to travel restrictions, whereas the central region remained relatively stable. By 2023, all three regions witnessed a significant rebound in efficiency. Notably, the central and western regions recorded the most pronounced improvements, while the eastern region exhibited more modest growth because it already operated near the efficiency frontier. Collectively, these findings suggest that while regional gaps remain prominent, the operational efficiency disparity has begun to narrow in the post-pandemic era.

4.4 Input and output improvement analysis

To further explore the potential for enhancing operational efficiency, this study conducts a detailed input and output improvement analysis of inefficient tourism firms in 2023. Since only 4 out of the 13 tourism listed firms reach operational efficiency in 2023 the study targets the remaining 9 inefficient firms for a comprehensive input and output improvement analysis. The corresponding results are presented in Table 2.

Table 2. Improvement ratios of input and output variables in 7 tourism listed firms in 2023.

		Input		Output	
DMU	**Efficiency score**	**Fixed assets**	**Employees**	**Tourism revenue**	**Tourists received**
EMSA	0.4903	-25.12%	-33.98%	0.00%	87.36%
GLLY	0.5573	0.00%	-32.35%	100.82%	0.00%
LJGF	0.7037	0.00%	-7.40%	73.71%	0.00%
YNLY	0.6293	-9.07%	-21.76%	0.00%	68.84%
XYWL	0.8524	-7.65%	0.00%	0.00%	25.66%
HSLY	0.5074	-9.20%	-37.45%	0.00%	102.22%
CBS	0.5618	0.00%	-24.35%	0.00%	112.68%
TMH	0.6652	-34.51%	-32.46%	0.00%	0.00%
ZJJ	0.6718	-37.36%	0.00%	42.10%	0.00%
Mean	0.6266	-13.66%	-21.08%	24.07%	44.08%

On the input side, fixed assets and labor require average reductions of 13.66% and 21.08% respectively to achieve optimality. Specifically, ZJJ and TMH exhibit the highest asset redundancies, while HSLY and EMSA suffer from severe overstaffing. Conversely, firms such as LJGF and XYWL operate at the efficient frontier for specific input dimensions. On the output side, average improvement potentials for revenue and tourist volume stand at 24.07% and 44.08%, indicating under-realized market capacity. While GLLY and LJGF demonstrate pronounced revenue gaps, they maintain optimal operational efficiency in tourist reception. These findings underscore the multidimensional nature of operational inefficiency. Certain entities like ZJJ struggle with localized resource imbalances despite reaching output benchmarks, whereas others such as EMSA exhibit systemic failure across all operational efficiency metrics. Such heterogeneity necessitates tailored strategic interventions rather than a uniform industry-wide approach.

5. Discussion and Recommendations

The results highlight that integrated cultural tourism firms outperform single-category scenery firms, as cultural elements significantly enhance product value and consumer engagement [8]. Spatially, a distinct efficiency gap exists between the eastern region and the central or western regions, driven by disparities in economic infrastructure and market maturity (Liao & Wang). Furthermore, the primary cause of organizational inefficiency is the misallocation of production resources, specifically labor redundancy and underutilized output potential. These findings provide a theoretical foundation for optimizing internal resource structures to improve total factor productivity within the tourism sector. Firms should first integrate local culture with digital technology to enhance service appeal and tourist satisfaction. Second, establishing cross-regional partnerships between eastern and western enterprises is essential to facilitate the transfer of advanced management expertise and capital. Finally, management must address labor redundancy by adopting intelligent systems, such as AI-driven customer service and automated ticketing. Combined with targeted marketing to increase tourist volume, these micro-level adjustments will optimize resource utilization and foster the sustainable development of Chinese tourism firms.

6. Conclusion

Using the SBM-DEA model, this study evaluates 13 listed tourism firms (2017–2023), revealing a low average efficiency of 0.4616. Operational efficiency is higher in integrated cultural firms and the eastern region. Inefficiency is primarily driven by labor redundancy and insufficient tourist reception. Consequently, firms should prioritize digital integration and cross-regional cooperation to optimize resource allocation. The study is constrained by a small sample of listed firms and a single-stage evaluation model. These factors limit the generalizability of the findings to the broader tourism industry. Future research should incorporate a more diverse range of enterprises and utilize multi-stage frameworks to capture more granular and longitudinal efficiency dynamics.

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