Measuring Performance Variability: A Meta-Heterogeneity Index Approach in Tourism Research

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Abstract

We propose the Meta-Heterogeneity Index (MHI), an index designed to uncover within groups performance disparities across destinations, firms, or regions, differences often overlooked by more conventional approaches. Using China's star-rated hotel panel data, we demonstrate the index's usefulness, showing how it separates efficiency change from technical change and identifies whether shortfalls stem from operations or technology. This fine detailed diagnosis equips destination managers and corporate decision-makers with clear priorities for reallocating resources or driving innovation. The MHI can be readily transferred to other tourism subsectors, offering researchers a practical tool for tracking competitiveness and enriching performance analysis in tourism management.

Keywords: Meta-Heterogeneity Index; Group heterogeneity; Performance Modeling; Efficiency; Tourism.

1 Introduction

Assessing performance is vital for the tourism sector, serving as the foundation for strategic planning and a critical driver of competitive advantage. Traditional models often struggle to reflect the complexity of tourism operations (Assaf and Tsionas, 2019), prompting demand for more robust tools. Non-parametric techniques such as Data Envelopment Analysis (DEA) play a central role in this context by comparing entities within a shared technology set and providing benchmarking diagnostics via linear programming (Song et al., 2012; Nurmatov et al., 2021).

When evaluating performance over time, DEA-based indices are widely used. Among them, the Malmquist Index (MI, Caves et al., 1982) remains the most popular, with decompositions (Färe et al., 1994; Ray and Desli, 1997) enabling richer insights. MI has been extensively applied to track productivity in tourism (Barros, 2005; Cracolici et al., 2007; Walheer and Zhang, 2018; Peypoch et al., 2021). However, conventional DEA indices like MI primarily capture between groups and temporal changes, offering limited detail on performance heterogeneity within groups. This limits their interpretive value in sectors like tourism, where standardized entities operate in highly diverse local environments.

In this note, we propose a novel DEA-based index, the Meta-Heterogeneity Index (MHI), to track performance shifts between and within groups.[1] MHI introduces a dual decomposition structure to separate group level technology shifts from entity level efficiency dynamics. This framework yields a more nuanced understanding of performance and supports targeted benchmarking across structurally comparable yet contextually heterogeneous entities. We illustrate this method using China's star-rated hotel sector, a nationally standardized system that enables cross provincial comparability, yet one that exhibits wide disparities in tourism infrastructure, service development, and regional economic conditions. This makes it an ideal empirical setting to test how performance gaps within groups evolve over time in structurally similar but contextually diverse environments.

The rest of the note is structured as follows. Section 2 presents the relevant literature, Section 3 defines the MHI framework, Section 4 illustrates its application using the Chinese star-rated hotel industry, and Section 5 concludes.

[1] There is a tradition in the efficiency and productivity literature to call 'meta' the concepts designed to take heterogeneity into account. See Walheer (2024a) for a detailed literature review.

2 Literature review and research gap

DEA-based measures, especially the Malmquist Index, remain the standard tool for productivity analysis in tourism (Peypoch & Solonandrasana, 2008; Assaf & Barros, 2011; Assaf & Tsionas, 2019). Yet conventional applications compare only aggregated units and ignore sizeable within group differences that arise from divergent management practices and resource mixes (Walheer & Zhang, 2018; Zha et al., 2019).

Accounting for heterogeneity is particularly crucial in tourism management because it reveals significant variations in operational efficiency, managerial practices, and strategic orientation among entities facing similar external conditions (Assaf and Tsionas, 2019; Arbelo et al., 2021). On the non-parametric side, recent methodological developments, such as the meta-frontier approaches by Oh and Lee (2010), Wang et al. (2023), and the technology convergence framework by Walheer (2024b), have significantly advanced between group performance assessments. However, these methods provide limited mechanisms for detailed within group analysis and often omit explicit procedures for systematically aggregating performance variations across entities. Addressing the identified within group heterogeneity enables tourism managers and policymakers to implement targeted interventions, optimize resource allocation, and enhance sector competitiveness and sustainability.

Moreover, numerous empirical studies (e.g., Luo et al., 2014; Dong et al., 2020; Zha et al., 2020; Peypoch et al., 2021) have identified and acknowledged regional and contextual heterogeneity as significant determinants of tourism productivity. While these studies effectively highlight the existence and relevance of such heterogeneity, their analytical frameworks typically remain constrained to within group comparisons or aggregate evaluations. Consequently, these approaches provide insufficient methodological tools to systematically measure within group performance variations, masking critical performance variations essential for fine-tuned management and policy strategies. Even more recent studies examining spatial correlations and regional heterogeneity within star-rated hotels (Tao et al., 2024; Tsai et al., 2025) underscore the importance of spatial performance disparities yet similarly fall short in providing robust methods for within group performance aggregation and comparative analysis.

To address these methodological limitations, this research introduces the Meta-Heterogeneity Index. Unlike previous indices that primarily focus on between group performance differences or overall productivity trends, the MHI explicitly captures and systematically aggregates both between and within group variations. Our approach fills a critical methodological gap by explicitly decomposing performance into components reflecting within group dynamics, enabling precise identification of internal variations often overlooked in previous frameworks. Using China's star-rated hotel industry as an illustrative context, the MHI extends existing productivity measures, offering enhanced analytical depth for tourism management research.

3 Methodology

We assume that we observe entities during T periods. As heterogeneity exists amongst entities, we consider that they can be partitioned into a certain number of groups. We aim to establish an index to compare the performance of the entities within each group over time. We label this new index the Meta-Heterogeneity Index (MHI). We assume that, in every group, entity i at period t produces Q outputs, captured by $\mathbf{y}_t^i$, using P inputs, captured by $\mathbf{x}_t^i$; and that $\mathbf{y}_t$ and $\mathbf{x}_t$ contain all the output-input vectors of the group. We start by defining the index based on technical efficiency. We then extend our framework by considering revenue and allocative efficiencies. To do so, we also introduce the notation for the output prices for the group: $\mathbf{p}_t$.

3.1 Technical efficiency

The new index is based on the concept of performance gaps and is defined for a specific entity i at time t as:

$$PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) = \frac{TE_t(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)}{TE_t^i(\mathbf{y}_t^i, \mathbf{x}_t^i)} \tag{1}$$

$PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)$ represents the performance gap between entity i and the group at time t. Here, $TE_t^i(\mathbf{y}_t^i, \mathbf{x}_t^i) = \sup\{\theta \mid \theta \mathbf{y}_t^i \in P_t^i(\mathbf{x}_t^i)\}$ stands for technical efficiency at the entity level while $TE_t(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)$ measures technical efficiency at the group level ($P_t^i(\mathbf{x}_t^i)$ is an output requirement set and represents the technology)[2]. A value of $PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) < 1$ indicates that the group performs better than entity i, whereas $PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) > 1$ implies that entity i outperforms the group.

[2] Group-level technical efficiency $TE_t(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)$ incorporates price information to weight each entity's contribution by its revenue share, whereas entity-level efficiency $TE_t^i(\cdot)$ is computed inde-

To compare the performance of entity i to the group between two time periods t and $t+1$, we consider the following ratios:

$$MHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) = \left[\left(\frac{PG_t^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{p}_{t+1})}{PG_t^i(\mathbf{y}_t, \mathbf{x}_t, , \mathbf{p}_t)} \right)^{-1} \times \left(\frac{PG_{t+1}^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{p}_{t+1})}{PG_{t+1}^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)} \right)^{-1} \right]^{1/2} \tag{2}$$

MHI^i reflects how entity i has changed its performance with respect to the group between t and $t+1$. When it is larger than 1, it means that entity i has worsened its performance with respect to the group. Conversely, a value smaller than 1 indicates that entity i has improved its performance with respect to the group. A value of 1 indicates similar performance changes.

A desirable feature of our index is that it can be decomposed into efficiency and technical changes as follows:

$$\begin{aligned} &MHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \\ &= MPEC^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \times MPTC^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \end{aligned} \tag{3}$$

$MPEC^i = \left(\frac{PG_{t+1}^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{p}_{t+1})}{PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)} \right)^{-1}$ measures how the gap in technical efficiency has changed between entity i and the group between t and $t+1$. When this index is smaller than 1 it means that entity i has a better efficiency change than the group. $MPTC^i = \left[\left(\frac{PG_t^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{p}_{t+1})}{PG_{t+1}^i(\mathbf{y}_{t+1}, \mathbf{x}_{t+1}, \mathbf{p}_{t+1})} \right)^{-1} \times \left(\frac{PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)}{PG_{t+1}^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)} \right)^{-1} \right]^{1/2}$ gives the change in technical gap between entity i and the group. Again, a value smaller than 1 implies a progression, while a value greater than 1 reveals a regression.

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pendently of prices. In practice, group-level efficiency is defined as a weighted sum:

$$TE_t(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) = \sum_{i=1} \frac{\mathbf{p}_t^{'} \mathbf{y}_t^i}{\mathbf{p}_t^{'} \sum_{i=1} \mathbf{y}_t^i} \times TE_t^i(\mathbf{y}_t^i, \mathbf{x}_t^i).$$

In an output-oriented DEA setting, each entity-level efficiency score TE_i^t is bounded below by 1, with 1 indicating full efficiency (i.e., the entity lies on the production frontier) and values greater than 1 indicating inefficiency. As such, the performance gap index PG_i^t can be greater or less than 1, depending on whether the entity outperforms or underperforms the group average.

3.2 Revenue and allocative efficiencies

Instead of technical efficiency, it is possible to define the performance gap from revenue or allocative perspectives.[3] We obtain the following:

$$RPG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) = PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) \times APG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t) \tag{4}$$

$RPG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)$ and $APG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)$ have analogous interpretations to $PG_t^i(\mathbf{y}_t, \mathbf{x}_t, \mathbf{p}_t)$, but in terms of revenue and allocative efficiency, respectively.

Next, we can define and decompose the index when using the revenue or allocative notions:

$$\begin{aligned} RMHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) &= RMPEC^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \\ &\quad \times RMPTC^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \end{aligned} \tag{5}$$

$$\begin{aligned} AMHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) &= AMPEC^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \\ &\quad \times AMPTC^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \end{aligned} \tag{6}$$

$RMPEC^i = \left(\frac{RPG_{t+1}^i(\mathbf{y}_{t+1},\mathbf{x}_{t+1},\mathbf{p}_{t+1})}{RPG_t^i(\mathbf{y}_t,\mathbf{x}_t,\mathbf{p}_t)}\right)^{-1}$ is the revenue efficiency change index, and $AMPEC^i = \left(\frac{APG_{t+1}^i(\mathbf{y}_{t+1},\mathbf{x}_{t+1},\mathbf{p}_{t+1})}{APG_t^i(\mathbf{y}_t,\mathbf{x}_t,\mathbf{p}_t)}\right)^{-1}$ is the allocative efficiency change index. Next, $RMPTC^i = \left[\left(\frac{RPG_t^i(\mathbf{y}_{t+1},\mathbf{x}_{t+1},\mathbf{p}_{t+1})}{RPG_{t+1}^i(\mathbf{y}_{t+1},\mathbf{x}_{t+1},\mathbf{p}_{t+1})}\right)^{-1} \times \left(\frac{RPG_t^i(\mathbf{y}_t,\mathbf{x}_t,\mathbf{p}_t)}{RPG_{t+1}^i(\mathbf{y}_t,\mathbf{x}_t,\mathbf{p}_t)}\right)^{-1}\right]^{1/2}$ and $AMPTC^i = \left[\left(\frac{APG_t^i(\mathbf{y}_{t+1},\mathbf{x}_{t+1},\mathbf{p}_{t+1})}{APG_{t+1}^i(\mathbf{y}_{t+1},\mathbf{x}_{t+1},\mathbf{p}_{t+1})}\right)^{-1} \times \left(\frac{APG_t^i(\mathbf{y}_t,\mathbf{x}_t,\mathbf{p}_t)}{APG_{t+1}^i(\mathbf{y}_t,\mathbf{x}_t,\mathbf{p}_t)}\right)^{-1}\right]^{1/2}$ are the revenue and allocative technical change indices.

Again, they have to be interpreted as MHI^i, $MPEC^i$, and $MPTC^i$ but when considering the revenue and allocative approaches.

Next, the following relationship, similar to the previous equation for the perfor-

[3] Revenue efficiency is defined as follows: $RE_t^i(\mathbf{y}_t^i, \mathbf{x}_t^i, \mathbf{p}_t) = \frac{R_t^i(\mathbf{x}_t^i,\mathbf{p}_t)}{\mathbf{p}_t^{\prime}\mathbf{y}_t^i}$, where $R_t^i(\mathbf{x}_t^i, \mathbf{p}_t) = \max_{\mathbf{y} \in P_t^i(\mathbf{x}_t^i)} \mathbf{p}_t^{\prime}\mathbf{y}$. Allocative efficiency is defined using technical and revenue efficiencies as follows $AE_t^i(\mathbf{y}_t^i, \mathbf{x}_t^i, \mathbf{p}_t) = \frac{RE_t^i(\mathbf{y}_t^i,\mathbf{x}_t^i,\mathbf{p}_t)}{TE_t^i(\mathbf{y}_t^i,\mathbf{x}_t^i)}$. We remark that the group concepts are also obtained as weighted sums.

mance gap, is satisfied:

$$\begin{aligned} RMHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) = MHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \\ \times AMHI^i(\mathbf{y}_t, \mathbf{y}_{t+1}, \mathbf{x}_t, \mathbf{x}_{t+1}, \mathbf{p}_t, \mathbf{p}_{t+1}) \end{aligned} \quad (7)$$

Note that it is fairly easy to see that similar connections hold true for the two decomposition factors. We summarize our new indices and their relationships in Table 1.

Table 1: Index summary and relationships

Orientation	**Index**	**Decomposition**
Technical	MHI	$= MPEC \times MPTC$
Revenue	$RMHI$	$= RMPEC \times RMPTC$
Allocative	$AMHI$	$= AMPEC \times AMPTC$
Relationships	$RMHI = MHI \times AMHI$ $RMPEC = MPEC \times AMPEC$ $RMPTC = MPTC \times AMPTC$	

3.3 Graphical intuition

Figure 1 shows the entity frontiers and the group technologies at t and $t{+}1$. The entity is at A and A', with radial projections $\widehat{A}$ and $\widehat{A'}$ on its own frontiers; the group points B and B' project to $\widehat{B}$ and $\widehat{B'}$ on the group frontiers. From the figure we have $TE_t^i = O\widehat{A}/OA$ and $TE_t = O\widehat{B}/OB$ (and analogously $TE_{t+1}^i = O\widehat{A'}/OA'$, $TE_{t+1} = O\widehat{B'}/OB'$). The performance gaps are $PG_t^i = TE_t/TE_t^i = (O\widehat{B} \cdot OA)/(OB \cdot O\widehat{A})$ and $PG_{t+1}^i = TE_{t+1}/TE_{t+1}^i = (O\widehat{B'} \cdot OA')/(OB' \cdot O\widehat{A'})$, so $MPEC^i = (PG_{t+1}^i/PG_t^i)^{-1} = (O\widehat{B} \cdot OA \cdot OB' \cdot O\widehat{A'})/(OB \cdot O\widehat{A} \cdot O\widehat{B'} \cdot OA')$. Let $d_s(OA)$ and $d_s(OA')$ be the lengths from O to the group frontier at period $s \in \{t, t{+}1\}$ along OA and OA'; then $MPTC^i = [\,d_t(OA)/d_{t+1}(OA) \cdot d_t(OA')/d_{t+1}(OA')\,]^{1/2}$, and $MHI^i = MPEC^i \cdot MPTC^i$.

3.4 Practical implementation

We compute output oriented Debreu and Farrell measures under constant returns to scale. For each entity i, efficiencies are obtained from the following linear programs,

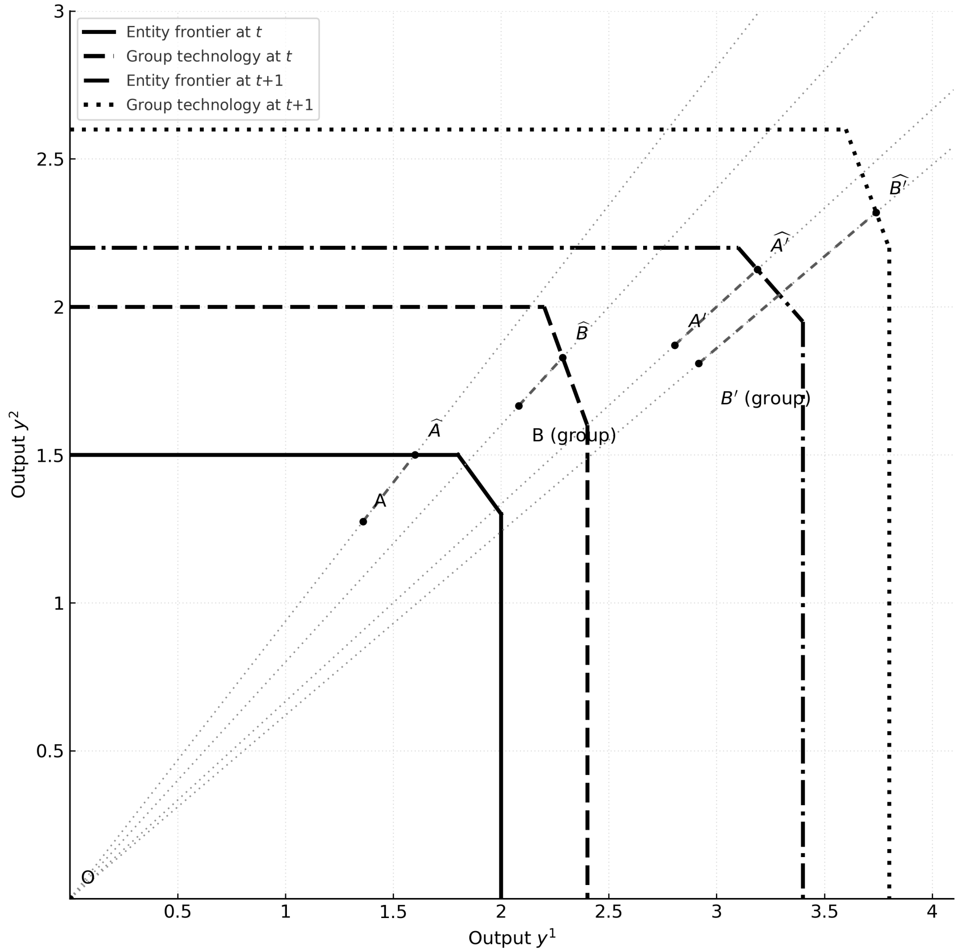

Figure 1: MHI Graphical Illustration

then used to build PG_i and MHI. The reference data are entity specific:

$$TE_t^i(\mathbf{y}_{t+1}^i, \mathbf{x}_{t+1}^i) = \max_{e,\,\lambda \geq 0} \left\{ e \;\middle|\; Y_t^i \lambda \geq e\, \mathbf{y}_{t+1}^i,\;\; X_t^i \lambda \leq \mathbf{x}_{t+1}^i \right\}. \tag{8}$$

$$RE_t^i(\mathbf{y}_{t+1}^i, \mathbf{x}_{t+1}^i) = \frac{\max_{\lambda \geq 0} \left\{ \mathbf{p}_t^\top Y_t^i \lambda \;\middle|\; X_t^i \lambda \leq \mathbf{x}_{t+1}^i \right\}}{\mathbf{p}_t^\top \mathbf{y}_{t+1}^i}. \tag{9}$$

Here X_t^i and Y_t^i contain only the inputs and outputs of entity i at time t, and $\lambda \geq 0$ are intensity weights. When a group reference is required, X_t and Y_t contain all entities at time t. Once these scores are computed, PG_i, RPG_i, APG_i, the meta heterogeneity indices MHI, $RMHI$, $AMHI$, and their decompositions ($MPEC$, $MPTC$, $RMPEC$, $RMPTC$, $AMPEC$, $AMPTC$) follow by direct calculation.

4 Empirical Application

We apply the Meta-Heterogeneity Index (MHI) to measure performance shifts in China's star-rated hotel industry between 2005 and 2022. This sector offers a unique empirical setting: while classification standards and regulatory frameworks are nationally unified, there exists substantial regional variation in economic structure, tourism infrastructure, and service development. These features make it especially well-suited for testing how within group performance gaps evolve over time and how they contribute to broader patterns in regional and national efficiency.

4.1 Data and Descriptive Statistics

The analysis utilizes a comprehensive provincial level dataset integrating three primary sources: China Tourism Statistics Yearbooks, the China Star Hotel Statistics Report, and the Wind Database, covering 30 provinces over the period 2005–2022.[4] Based on the National Statistics Bureau of China's classification, the Eastern region comprises 11 provinces (e.g., Beijing, Shanghai), the Central region includes 8 provinces (e.g., Henan, Hunan), and the Western region contains 11 provinces (e.g., Sichuan, Yunnan).

Following established literature (Dong et al., 2020; Peypoch et al., 2021; Walheer & Zhang, 2018), we use two primary outputs, revenues from room and meal services,

[4]Tibet was excluded due to data incompleteness.

as proxies for hotel service quantity and quality. Consistent with previous studies, we use room and meal revenues as outputs capturing volume and willingness to pay (Hwang & Chang, 2003; Hsieh & Lin, 2010); without guest level provincial data, this is the most viable specification, DEA's multi-input structure (capacity, labor, capital) controls for scale. Star-rated hotels differentiate primarily through service quality, reflected in pricing and subsequently in revenue (Walheer & Zhang, 2018). Inputs include labor (number of employees) and capital (fixed assets), consistent with common practice in DEA-based tourism studies (Peypoch & Solonandrasana, 2008; Assaf & Barros, 2011).

Table 2: Statistical description of input and output variables.

			Trimmed Mean(10%)	St.Dev	Min	Max
2005	O1: Sales for Room (million RMB)	Output	1,989.51	2,507.98	128.43	9,633.45
	O1: Sales for Meal (million RMB)	Output	1,488.46	1,498.21	92.68	5,155.17
	I1: No. of Employed Persons (thousand person)	Input	459,692.76	384,229.02	51,440	1,788,170
	I2: Fixed Assets (million RMB)	Input	10,813.07	13,374.39	935.18	61,090.22
2022	O1: Sales for Room (million RMB)	Output	1,463.51	1,246.10	144.71	4,764.46
	O1: Sales for Meal (million RMB)	Output	1,423.18	1,454.27	33.83	5,387.50
	I1: No. of Employed Persons (thousand person)	Input	197,413.79	144,050.64	13,000	612,000
	I2: Fixed Assets (million RMB)	Input	12,347.41	11,183.85	1,043	52,132
C	O1: Sales for Room (million RMB)	Output	1,451.65	671.85	291.30	3,457.00
	O1: Sales for Meal (million RMB)	Output	1,446.61	730.02	203.63	3,952.58
	I1: No. of Employed Persons (thousand person)	Input	295,383.42	133,929.14	43,000	601,900
	I2: Fixed Assets (million RMB)	Input	2,954.00	3,196.16	2,949.63	20,025
E	O1: Sales for Room (million RMB)	Output	4,441.44	3,320.10	335	13,793.61
	O1: Sales for Meal (million RMB)	Output	4,175.38	3,029.98	247.00	11,224.89
	I1: No. of Employed Persons (thousand person)	Input	627,255.77	414,241.07	57,000	1,886,420
	I2: Fixed Assets (million RMB)	Input	24,235.46	16,382.45	3,441.11	74,558.76
W	O1: Sales for Room (million RMB)	Output	1,233.85	909.49	74.00	3,979.25
	O1: Sales for Meal (million RMB)	Output	981.06	787.93	33.83	3,874.97
	I1: No. of Employed Persons (thousand person)	Input	235,676.42	221,577.81	11,000	2,072,000
	I2: Fixed Assets (million RMB)	Input	7,309.79	5,494.86	420.00	26,158.34
Total	O1: Sales for Room (million RMB)	Output	2,326.35	2,684.04	74.00	13,793.61
	O1: Sales for Meal (million RMB)	Output	2,159.95	2,482.22	33.83	11,224.89
	I1: No. of Employed Persons (thousand person)	Input	385,751.31	348,790.03	11,000	2,072,000
	I2: Fixed Assets (million RMB)	Input	13,307.67	13,627.73	420.00	74,558.76

Table 2 highlights two important trends. First, there is a slight decrease in average room revenue, with a relative increase in meal revenue, which aligns with a broader shift in hotel operations toward diversified hospitality offerings. This trend reflects a repositioning of food and beverage (F&B) services as revenue-generating components, consistent with emerging multi-service business models in upscale tourism sectors. Second, fixed assets increased significantly, while employee numbers generally declined, indicating capital-intensive development and more efficient labor utilization in line with industry restructuring (Ashraf et al., 2025; Walheer and Zhang, 2018).

4.2 Results

Meta-Heterogeneity Index. Table 3 presents provincial-level MHI results, providing deeper insights into how individual provinces deviate from their respective regional performance benchmarks.[5]

Table 3: MHI results by province

Province	Region	MHI	RMHI	AMHI	Province	Region	MHI	RMHI	AMHI
Anhui	C	0.75	0.67	0.97	Beijing	E	0.97	1.02	0.94
Henan	C	0.80	0.73	0.94	Guangdong	E	0.97	0.91	1.11
Shanxi	C	0.47	0.47	0.94	Hainan	E	1.74	1.80	1.03
Heilongjiang	C	1.23	1.25	1.10	Shanghai	E	0.83	0.95	1.03
Hubei	C	0.83	0.95	1.11	Fujian	E	1.05	1.10	1.10
Hunan	C	0.91	0.77	0.86	Liaoning	E	1.18	1.12	0.88
Inner Mongolia	C	1.09	0.87	0.86	Zhejiang	E	1.04	1.12	0.98
Jiangxi	C	1.04	1.14	1.10	Tianjin	E	0.80	0.76	1.15
Jilin	C	1.09	1.07	0.88	Hebei	E	0.85	0.77	0.74
					Shandong	E	1.13	0.91	0.72
Yunnan	W	0.78	0.76	1.06	Ningxia	W	0.91	0.52	0.73
Guizhou	W	0.93	1.05	1.01	Shaanxi	W	1.79	1.75	0.97
Chongqing	W	1.06	0.93	0.96	Gansu	W	1.31	1.16	0.99
Sichuan	W	1.23	1.16	1.03	Qinghai	W	1.18	1.25	0.98
Xinjiang	W	1.01	0.91	0.93					

Note: MHI > 1 indicates performance regression relative to regional benchmarks, and MHI < 1 indicates improvement.

The MHI confirms pronounced disparities within regions. Shanxi and Ningxia achieve substantial performance gains (MHI < 1) by effectively aligning hotel offerings with targeted regional advantages: Shanxi through improved allocative efficiency via heritage-based branding ("San Jin") and Ningxia via resource allocation supporting specialized wine tourism. In contrast, Hainan and Shaanxi experience performance declines. Hainan's regression stems mainly from decreased technical and revenue efficiencies linked to reliance on volatile seasonal demand, characterized by significant fluctuations in quarterly tourist arrivals (highest in Q1/Q4 and lowest in Q2/Q3) and occupancy rates (routinely above 65% in peak seasons but below 50% off-peak), while Shaanxi's extensive hospitality infrastructure investments have yet to yield sufficient

[5] **Data note.** The descriptive indicators in this section are compiled from Provincial/National Tourism Yearbooks accessed via Wind and CEIC; city-/segment-level hotel metrics draw on STR and UHC Consulting; policy details for Yunnan reference the China Tourism Academy (2023) and the Yunnan "Smart Tourism Three-Year Action Plan".

operational returns. Guangdong faces allocative efficiency losses as its rapid shift to high-end segments outpaces effective resource reallocation, evident from the substantial growth in five-star hotel numbers (from 32 to 93) without proportional revenue gains, alongside persistent underperformance in lower-tier segments, whereas Yunnan notably enhances its technical efficiency through targeted technological innovations, despite modest overall improvements.

These province-specific insights, typically obscured by conventional regional aggregates, underscore the MHI's capacity to isolate precise drivers of performance variations, offering actionable guidance for targeted strategic interventions in tourism management.

Decomposition insights. Figure 2 displays efficiency-change (PEC) and technical-change (PTC) gaps for the MHI, RMHI and AMHI, each expressed as index − 1. Three points emerge.

1. **Dispersion within regions dominates.** A handful of provinces deviate by more than ±0.15 from their regional frontier, showing that the usual East, Central, West split hides substantial heterogeneity.

2. **Leaders from efficiency change; laggards from allocative frictions.** Shanxi and Ningxia post the deepest negative PEC gaps across all orientations, reflecting productive cultural tourism upgrades and lean staffing. By contrast, Hainan exhibits large positive PEC gaps (+1.16, +0.84), while its AMPEC bar is slightly negative; the province reallocates assets reasonably well but suffers operational drag, reflecting over reliance on seasonal demand. This reading is supported by pronounced peak to off season swings in arrivals and hotel use, with sustained highs in the first and fourth quarters and lows in the second and third (Chen et al., 2017; Zhou et al., 2024). Guangdong shows the mirror image: a negative MPEC with positive RMPEC and AMPEC, indicating that rapid moves to the high end outpaced the rebalancing of labour and capital. This pattern is supported by official statistics and academic work showing upscale capacity outpaced demand, muted revenue gains, and slack in mid scale segments, with city level disparities in the Pearl River Delta (Dongguan, Foshan, and Zhongshan) pointing to underperformance (Tsai et al., 2025). Together these features align with positive RMPEC and AMPEC and a negative MPEC.

3. **Technological progress is uneven.** Yunnan achieves the largest negative PTC values, confirming pay-offs from digital and smart-hotel investments, such as the province-wide integration of the digital platform "One Mobile Phone Touring Yunnan" into star-rated hotels since 2015. Shaanxi and Gansu sit at the other extreme, indicating that recent capacity expansions have yet to translate into productivity.

The decomposition therefore identifies **where**(province) and **how**(efficiency, technology, allocation) performance gaps arise, giving managers and policymakers a detailed map for targeted interventions, insight that aggregate DEA or meta-frontier scores cannot supply.

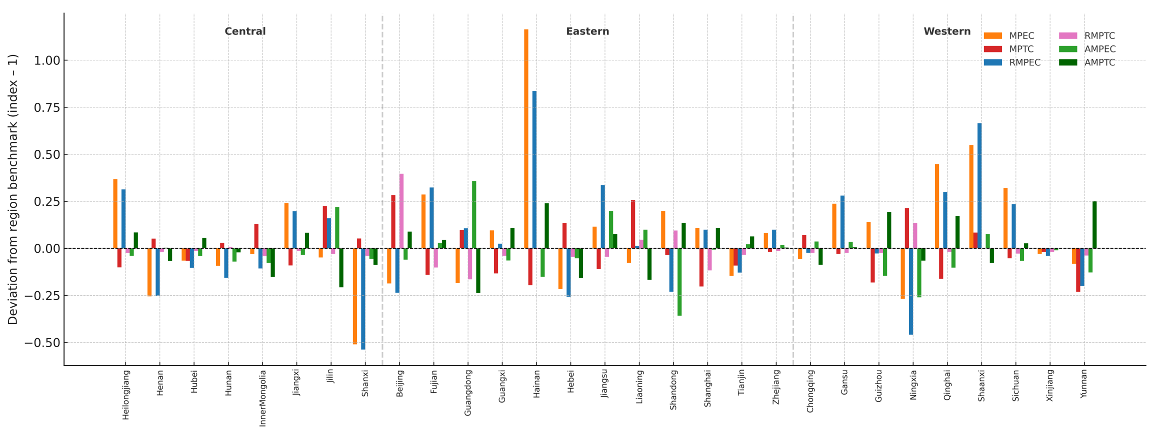

Figure 2: Provincial MHI Decomposition by Region

Robustness Check. To assess the robustness of these findings, we recalculated the indices excluding the COVID-19 years (2020–2022). Results remained consistent, affirming that observed performance variations are structural and methodologically robust rather than driven by recent shocks.

5 Conclusion and Future Research

In this note, we introduced the Meta-Heterogeneity Index, a new DEA-based method specifically designed to enhance within group performance analysis, complementing existing methods that primarily focus on between group comparisons among tourism entities. Unlike traditional approaches that primarily focus on aggregate or between group analyses, the MHI explicitly captures nuanced performance dynamics within groups. Our empirical illustration, applied to China's star-rated hotel sector from 2005 to 2022, demonstrated the MHI's practical relevance by uncovering significant regional and provincial performance heterogeneity, previously obscured by conventional methodologies.

The analysis revealed performance regressions driven by diversification strategies and substantial new investments, underscoring the MHI's capability to pinpoint precise managerial and policy areas needing attention. By decomposing the index into allocative and technical efficiency components, the MHI offers actionable insights into internal dynamics influencing performance, such as technological innovation and resource reallocation, enabling targeted interventions tailored to each region's characteristics.

Several tourism management implications arise from our findings. First, diversification strategies in hospitality enterprises should align closely with core competencies and market demands to ensure consistent performance outcomes and minimize fluctuations in operational efficiency. Second, targeted regional investment and policy initiatives, informed by MHI analysis, can address specific local needs, optimizing resource allocation and fostering balanced tourism growth. Third, by identifying leading and lagging provinces, policymakers can develop customized interventions, including strategic infrastructure investments and technology adoption programs, enhancing overall sector resilience and competitiveness.

Looking ahead, future research could expand the application of the MHI to other tourism subsectors and further validate its generalizability beyond the Chinese context. Integrating direct quality measures, if available, would strengthen the robustness of performance evaluations. Moreover, combining the MHI framework with emerging digital data sources could enhance real-time responsiveness to evolving market dynamics, offering new avenues for evidence-based, sustainable tourism management practices. Finally, the index's adaptable design means it can readily be applied across other tourism domains, such as attractions, transport services, and destination management, broadening its value for sector-wide performance analysis.

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