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Benchmarking a Seasonal Resort Against Its Own Operating Months Through Dynamic Network Data Envelopment Analysis

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Abstract

Hotel efficiency studies typically benchmark properties against one another, yet much of what such cross-sectional comparisons credit to management in fact belongs to the setting — the destination, the segment, the size of the asset. This study inverts the design. It takes an operating month of a single year-round Mediterranean resort as the decision-making unit, so that the homogeneity data envelopment analysis requires becomes a property of the sample rather than an assumption to be defended, and the within-year variation a seasonal property exists to manage is preserved rather than averaged away. Sixty consecutive months are evaluated with radial models and a two-stage network slacks-based measure, extended by contemporaneous conditions that hold each month accountable for the forward-booking and reputation stocks it inherits and passes on, with inputs measured at constant prices. Scale efficiency averages 0.764 and carries most of the shortfall, an index of the operating leverage the property sustains through its low season. The binding stage alternates with the calendar, and pricing the inherited stocks reorders the panel even though it barely moves the mean. Treating the operating month as the unit offers a transferable route to efficiency measurement for seasonal firms.

Keywords: Hotel efficiency; Dynamic network DEA; Slacks-based measure; Seasonality; Carry-over

JEL Classification: C61; D24; L83; Z31

1. Introduction

In August a 350-room resort on the Turkish Mediterranean coast runs at eighty-four per cent occupancy with a headcount near three hundred; in January it runs at thirty-seven per cent with just over two hundred on the payroll. Occupancy moves by a factor of 2.2 across the calendar, staffing by only 1.4, and winter energy per occupied room-night is more than half again as high. A manager asking whether last January was well run has no natural comparison: last August was a different business and the hotel down the road a different asset, and the standard tools were not built to answer the question.

Frontier analysis has been applied to hotels for three decades, almost always across properties and so resting on sample homogeneity (Neves and Lourenço 2009; Manasakis et al. 2013). The assumption is heavy: across four hundred Spanish hotels, the destination, not management, was the principal source of variation (Lado-Sestayo and Fernández-Castro 2019). The correction layers the literature has added leave the manager's question about January unanswered.

There is an alternative. If comparability is the problem it can be removed rather than adjusted for, by making the decision-making unit an operating month of one property: every unit is then the same asset, management, and capacity, and the homogeneity assumption of Charnes et al. (1978) holds by construction. What is new is the resolution: longitudinal hotel studies work at the firm-year and average away the within-year variation a seasonal property exists to manage (Günaydın et al. 2022).

Network models that split the production of occupancy and covers from their conversion into revenue locate inefficiency in one stage (Tan and Despotis 2021; Zhu et al. 2023; Choi and Kim 2024); this study reads that decomposition month by month.

The intertemporal dimension is where the standard apparatus stops: a month inherits a booking position and a reputation and passes on others. The dynamic treatment of Tone and Tsutsui

(2010, 2014) presupposes periods nested within units, unavailable where the periods are the units, so we treat the inherited stock as a non-discretionary input (Banker and Morey 1986) and the bequeathed stock as a desirable output.

Because statutory wage revisions and an energy shock fall inside the window, each cost line is deflated by its own price index, so price movements are not read as inefficiency (Coelli et al. 2005).

What emerges from the sixty months is not what the cross-sectional literature would predict: the shortfall is almost entirely scale rather than technique, the binding stage alternates with the season, productivity grows almost wholly through frontier shift, and the intertemporal condition proves decisive while the stage weights do not.

This study asks whether the shortfall is one of scale or technique, whether the binding stage holds across the calendar or moves with the season, and how far the ranking turns on pricing the stocks each month inherits and passes on. Sections 2 to 5 review the literature, develop the models, apply them, and conclude.

2. Literature Review

The review is organised around the three decisions that distinguish this study: the operating month as the unit, the operational and revenue-conversion stages, and the treatment of forward demand and reputation as stocks passing between periods. Each subsection marks what the field has settled and where it stops.

2.1. Frontier Measurement of Hotel Efficiency

Non-parametric frontier analysis entered hospitality research early and remains dominant, from the first Turkish Riviera application (Tarım et al. 2000) through balanced-scorecard integration for Korean chains (Min et al. 2008) to scale-versus-technical decompositions across firm panels (Neves and Lourenço 2009).

Later applications widened the geographic range without changing the design, from all-inclusive Turkish coastal properties (Tumer 2010) to Cretan hotels (Manasakis et al. 2013) and Turkish provinces over 2007–2010 (Keskin Benli 2012).

The unit throughout is the firm, or in aggregate work the region, and the window a single year or short firm-year panel.

2.2. The Comparability Problem in Cross-Sectional Samples

Because DEA builds the frontier from the sample, the homogeneity of the units governs what a score means, and the literature has added correction layers rather than removing the heterogeneity, the destination-dominance result above (Lado-Sestayo and Fernández-Castro 2019) being the clearest symptom.

Related corrections address spatial dependence (Wang et al. 2020), technological heterogeneity through metafrontiers (Hernández-Guedes et al. 2026), and manual versus non-manual labour (Huang 2017), none removing the heterogeneity they correct for.

Removing heterogeneity by construction, rather than correcting for it after the fact, is untried in the hotel literature.

2.3. Opening The Black Box: Network DEA in Hospitality

The two-stage representation is now established, from relational network DEA for Taiwanese hotels (Hsieh and Lin 2010) to bi-objective operations-and-marketing models (Yin et al. 2020), vertical extensions with shared inputs (Zhu et al. 2023), and departmental bootstrap scores (Yin et al. 2015).

The results converge on one diagnosis: revenue conversion is the weaker stage, whether in the UK (Tan and Despotis 2021), among Taiwanese hotels unable to turn service capability into earnings (Zhu et al. 2023), or in lower-tier hotels that build quality but fail to price it (Choi and Kim 2024). Kim and Chung (2022) placed satisfaction between the stages.

The specification is settled and robust across markets; what is untried is applying it to one property's own time series, locating the weaker stage within a hotel's calendar.

2.4. Intertemporal Structure: Dynamic Models and Carry-Overs

Because hotel output is perishable, each period is conditioned by the previous one. The dynamic apparatus of Tone and Tsutsui (2010, 2014) links a unit's consecutive periods, and applied to hotels it has isolated sustained performers (Wu et al. 2013) and yielded more stable efficiencies than static models (Shieh et al. 2017; Wu and Lin 2022).

It has since been paired with time-window designs for Mexican beach destinations (Flegl et al. 2026) and built into a full dynamic network SBM for the Chinese power industry (Meng and Pang 2022), the closest precedent for the structure used here.

A structural limitation runs through this work. The apparatus presupposes periods nested within decision-making units, so continuity binds a unit's own intensity vectors; where the periods are the units it is unavailable, and no adaptation has been proposed.

2.5. Longitudinal Designs and The Resolution of The Panel

Treating one unit observed in different periods as distinct units underlies window analysis (Charnes et al. 1985), used at growing scale in bootstrapped provincial panels (Li et al. 2022) and life-cycle trajectories (Yin et al. 2015).

The closest design is Günaydın et al. (2022), comparing all-inclusive and bed-and-breakfast operations in Türkiye over nine years with multi-period DEA and a Malmquist decomposition; evaluating summer separately, they found such operations scaled to run year-round and called for strategies to mitigate seasonality.

In every case the unit stays the firm-year or region-year, averaging over the within-year variation a seasonal resort must manage; monthly resolution is absent from the literature.

2.6. Variable Selection, Input Prices, and Intangible Stocks

Specification choices have drawn attention, from variable screening (Hu and Cai 2004) to composite slacks indices (El Kadiri Boutchich 2024), and ignoring an undesirable output overstates efficiency (Hernández-Guedes et al. 2026).

Intangible stocks have entered only recently: Kim and Chung (2022) and Choi and Kim (2024) place satisfaction or quality between the two stages within one period, but neither treats reputation as a stock a month inherits and bequeaths.

One measurement issue is largely unaddressed. Cost lines routinely proxy for input quantities without deflation by input-specific price indices. In stable prices the omission is harmless; under statutory wage revisions or energy shocks it is not (Coelli et al. 2005). No hotel study reviewed here reports such a correction.

2.7. Synthesis and Research Gap

Table 1 positions the closest prior studies along the dimensions that matter here: the unit of assessment, the temporal resolution, the model's internal structure, and the treatment of intertemporal stocks.

Table 1. Positioning of The Closest Prior Studies.

Study	Setting	DMU and n	Period	Method	Internal / intertemporal structure
Tarım et al. (2000)	Antalya, Türkiye	4–5★ hotels	1 year	Output-constrained DEA	Black box; static
Min et al. (2008)	Korea	6 luxury chains	Multi-year	CCR, BCC + BSC	Black box; static
Neves and Lourenço (2009)	Worldwide	83 firms	3 years	DEA	Black box; longitudinal
Hsieh and Lin (2010)	Taiwan	International tourist hotels	1 year	Relational network DEA	Two-stage; static
Tumer (2010)	Türkiye, coastal	4–5★ resorts	1 year	DEA (modified RevPAR)	Black box; static
Keskin Benli (2012)	Türkiye, provinces	Provinces	2007–2010	DEA + Malmquist	Black box; annual panel
Wu et al. (2013)	Taiwan	80 hotels	2006–2010	Dynamic + super-efficiency DEA	Black box; carry-over
Manasakis et al. (2013)	Crete, Greece	50 hotels	1 year	DEA	Black box; static
Yin et al. (2015)	Taipei, Taiwan	20 hotels	Multi-year	Two-layer bootstrap DEA	Departmental; life-cycle
Huang (2017)	Taiwan	Tourist hotels	1 year	Hybrid DEA	Black box; static
Shieh et al. (2017)	Taiwan	45 hotels	2002–2011	Four-stage + dynamic DEA	Black box; carry-over

Lado-Sestayo and Fernández-Castro (2019)	Spain	400 hotels	1 year	Four-stage DEA	Black box; static
Yin et al. (2020)	Taiwan	68 hotels	2011	Two-stage network DEA	Two-stage; static
Tan and Despotis (2021)	United Kingdom	Hotel industry	1 year	Network DEA, weak link	Two-stage; static
Kim and Chung (2022)	Korea	Hotels	1 year	Network DEA	Two-stage, satisfaction link
Günaydın et al. (2022)	Türkiye	AI vs. B&B operations	9 years	Multi-period DEA + Malmquist	Black box; seasonal split
Meng and Pang (2022)	China, power sector	Provinces	Multi-year	Dynamic network SBM	Two-stage + carry-over
Zhu et al. (2023)	Taiwan	70 hotels	2014	Hierarchical network DEA	Multi-level; static
Choi and Kim (2024)	Korea	57 hotels	1 year	Two-stage network DEA	Two-stage, quality link
Flegl et al. (2026)	Mexico	20 beach destinations	2010–2019	Dynamic two-stage DEA	Two-stage + window
This study	Antalya, Türkiye	60 operating months of one property	2021–2025	Radial, network SBM, carry-over, Malmquist, window	Two-stage + carry-over, month as DMU

Notes: AI = all-inclusive; B&B = bed and breakfast; BSC = balanced scorecard; SBM = slacks-based measure. Studies are ordered chronologically. Meng and Pang (2022) is included as the closest precedent for the combined network-and-dynamic structure, though outside hospitality.

The gaps intersect. Comparability is everywhere corrected for and nowhere removed by construction, which the monthly single-property panel does at the cost of one-asset inference. The finest longitudinal grain remains the firm-year, which averages away the seasonal cycle; and the dynamic models presuppose periods nested within units, unavailable where the periods are the units.

A monthly panel of one property makes homogeneity automatic and preserves the seasonal cycle, but dissolves the standard dynamic construction. This study adopts the settled network specification, applies it at monthly resolution to a single asset, and replaces the continuity conditions with contemporaneous constraints on the stocks a month inherits and produces.

3. Methodology

The measurement problem has three layers. A radial assessment against the property's own history separates the technical shortfall from operating at the wrong scale; a two-stage network representation splits expenditure-to-volume from volume-to-revenue conversion; and two contemporaneous constraints hold each month accountable for the stocks it inherits and passes on. Productivity change, temporal stability, and a verification protocol complete the design.

3.1. Research Design: The Month As The Decision-Making Unit

Cross-sectional studies must defend the comparability of properties differing in size, segment, ownership, and location. The present design inverts the problem: the unit is an operating month of one property, giving sixty units from January 2021 to December 2025. Every unit is the same asset, management, and capacity, so the homogeneity assumption of Charnes et al. (1978) holds by construction; what remains is comparability across time, for which window analysis (Charnes et al. 1985) and one-set pooling (Pastor and Lovell 2005) are precedents.

Confining inference to one asset raises an external-validity question. The claim is analytic rather than statistical (Yin 2018): the panel is a setting in which a measurement logic can be shown to operate and then transferred to comparable seasonal properties, trading statistical breadth for internal validity and seasonal resolution.

The specification is comfortably identified: with four inputs and two outputs, the rule $n \geq \max\{m \cdot s, 3(m + s)\}$ of Cooper et al. (2007) asks for eighteen units against sixty. Seasonality is not netted out but measured, the monthly demand variation being the environment management must convert into revenue. Provincial foreign arrivals are held outside the frontier models and kept only for context: entering the series would confound the demand environment with the efficiency of the response to it, and the same-calendar-month comparisons of Section 3.8 already absorb its seasonal component.

Internally the property is a two-stage network: an operating stage converts the four cost inputs into occupied room-nights and covers, and a revenue-conversion stage turns those volumes, with the price environment, into rooms and food-and-beverage revenue. The intermediates link the stages, locating inefficiency in one stage rather than the whole.

3.2. Notation

Months are indexed by $j \in J = \{1, \dots, 60\}$, and the unit under evaluation is written as month 0. Each month consumes the input vector $x_j = (x_{1j}, \dots, x_{4j})^\top$, whose components are staff cost

x_1 , energy cost x_2 , other operating cost x_3 , and marketing and distribution cost x_4 . It produces the intermediate vector $z_j = (z_{1j}, z_{2j})^\top$, consisting of occupied room-nights z_1 and covers served z_2 , and the final output vector $y_j = (y_{1j}, y_{2j})^\top$, consisting of rooms revenue y_1 and food-and-beverage revenue y_2 .

Two carry-over stocks connect month t to month $t + 1$. They are collected in $c_j = (c_{1j}, c_{2j})^\top$, where c_1 is the month-end forward-booking position and c_2 the online guest-review score. A superscript distinguishes the stock a month inherits, c^{in} , from the stock it bequeaths, c^{out} . Input prices are indexed by p_{ij} and the corresponding constant-price quantities by x_{ij}^r .

On the model side, λ denotes the intensity vector of the radial programmes, while $\lambda_j^{(1)}$ and $\lambda_j^{(2)}$ denote the stage-specific intensities of the network programmes. Input slacks are written s_i^- , with an asterisk added at the optimum. The endogenous benchmark level of intermediate product p is ζ_p . Multipliers are u for outputs and v for inputs, with u_0 the free intercept of the variable-returns programme. Stage weights are w_1 and w_2 , stage scores θ_1 and θ_2 , and the composite network score ρ_0 . Distance functions relative to the pool of year a are written $D^a(\cdot)$. Monetary variables enter the programmes in thousands of euros; m and s denote the number of inputs and outputs.

3.3. Constant-Price Measurement of Inputs

Frontier models need input quantities; where expenditure stands in, input-price movements enter as changes in technical performance (Coelli et al. 2005). The concern is not marginal here, with wage revisions twice a year and a sharp 2022–2023 energy rise, so each cost line is deflated by its own price index to the base month, January 2021,

$$x_{ij}^r = \frac{x_{ij}}{p_{ij}}, \quad p_{i,base} = 1, \quad i = 1, \dots, 4 \quad (1)$$

with the wage index applied to x_1 , the wholesale energy series to x_2 , and a general cost index to x_3 and x_4 . All programmes below take x_{ij}^r as the input vector; nominal series are retained

only for description. Skipping this step has a specific and diagnosable consequence in a single-property panel: the earliest year, whose input prices are lowest, is pushed onto the frontier for reasons that have nothing to do with how it was run.

3.4. The Global Production Possibility Set

All sixty months are pooled into one technology set. Under constant returns to scale this gives

$$T^G = \{(x, y) : x \geq \sum_{j \in J} \lambda_j x_j, y \leq \sum_{j \in J} \lambda_j y_j, \lambda \geq 0\} \quad (2)$$

and the efficiency of month 0 is the smallest radial contraction of its input vector that keeps the contracted point inside the set,

$$\theta_0^{CCR} = \min\{\theta : (\theta x_0, y_0) \in T^G\} \quad (3)$$

Because the reference set spans the whole horizon, a score in one month is directly comparable with one five years later — the property that makes the pooled design work (Pastor and Lovell 2005). Distance functions of the form (3), against T^G or restricted pools, recur in every model below: the Malmquist index (Section 3.8) uses annual pools and the window analysis rolling twelve-month pools, but the object computed is the same.

3.5. Radial Black-Box Models

Linear-programming duality turns (3) into the multiplier problem of Charnes et al. (1978), in which the evaluated month chooses the weights that show it most favourably, subject to those weights not making any month appear better than fully efficient,

$$\begin{aligned} \theta_0^{CCR} &= \max_{u,v} u^\top y_0 \\ \text{s.t. } & v^\top x_0 = 1, u^\top y_j - v^\top x_j \leq 0 \quad \forall j \in J, u \geq 0, v \geq 0 \end{aligned} \quad (4)$$

The normalisation $v^\top x_0 = 1$ fixes the scale of the weights and makes the objective read directly as the efficiency score. Adding a free intercept relaxes the constant-returns assumption and produces the variable-returns model of Banker et al. (1984),

$$\begin{aligned} \theta_0^{BCC} &= \max_{u,v,u_0} u^\top y_0 + u_0 \\ \text{s.t. } & v^\top x_0 = 1, u^\top y_j + u_0 - v^\top x_j \leq 0 \quad \forall j \in J, u \geq 0, v \geq 0, u_0 \text{ free} \end{aligned} \quad (5)$$

The ratio of the two isolates the part of the shortfall attributable to scale rather than technique,

$$SE_j = \frac{\theta_j^{CCR}}{\theta_j^{BCC}}, \quad 0 < SE_j \leq 1 \quad (6)$$

In a cross-section this decomposition asks whether a property is the right size; here it asks something else. With capacity fixed at 350 rooms, a low scale-efficiency score records the cost of running that capacity against seasonal demand, not a statement about the asset's size.

3.6. Static Network Slacks-Based Measure

A radial score compresses the operation into one number, and a month can offset weakness in one part of the business with strength in another without the aggregate revealing it (Färe and Grosskopf 2000). The network model follows the slacks-based measure of Tone (2001) in the two-stage form of Tone and Tsutsui (2009), which prices every slack individually and evaluates the two stages separately. Stage 1 uses x_1 , x_2 , and x_3 to produce z_1 and z_2 . Stage 2 takes those volumes together with x_4 and produces y_1 and y_2 . The intermediate flow is treated as a free link, meaning its benchmark level ζ_p is chosen by the programme rather than fixed at the observed value, so that the two stages are optimised jointly rather than in sequence. All slacks-based programmes are solved under variable returns to scale, since one carry-over is a bounded index and convex combinations of bounded ratios are meaningful only in that regime (Hollingsworth and Smith 2003). With stage weights $w_1 = w_2 = 0.5$ in the baseline, the input-oriented objective is

$$\rho_0 = \min w_1 \left[1 - \frac{1}{3} \sum_{i=1}^3 \frac{s_i^-}{x_{i0}^r} \right] + w_2 \left[1 - \frac{s_4^-}{x_{40}^r} \right] \quad (7)$$

subject to the Stage-1 balance, link, and convexity conditions,

$$\begin{aligned} \sum_{j \in J} \lambda_j^{(1)} x_{ij}^r &= x_{i0}^r - s_i^- \quad (i = 1, 2, 3), \\ \sum_{j \in J} \lambda_j^{(1)} z_{pj} &= \zeta_p \quad (p = 1, 2), \quad \sum_{j \in J} \lambda_j^{(1)} = 1, \end{aligned} \quad (8)$$

and to the corresponding Stage-2 conditions,

$$\begin{aligned} \sum_{j \in J} \lambda_j^{(2)} z_{pj} &= \zeta_p \quad (p = 1, 2), \quad \sum_{j \in J} \lambda_j^{(2)} x_{4j}^r = x_{40}^r - s_4^-, \\ \sum_{j \in J} \lambda_j^{(2)} y_{rj} &\geq y_{r0} \quad (r = 1, 2), \quad \sum_{j \in J} \lambda_j^{(2)} = 1, \end{aligned} \quad (9)$$

with all intensities and slacks non-negative. The common value of ζ_p in (8) and (9) is what joins the two programmes: whatever volume the first stage is judged capable of producing is exactly the volume the second stage is required to work with. Writing s_i^{-*} for the optimal slacks, the stage scores and the composite follow as

$$\begin{aligned}\theta_1 &= 1 - \frac{1}{3} \sum_{i=1}^3 \frac{s_i^{-*}}{x_{i0}^r}, & \theta_2 &= 1 - \frac{s_4^{-*}}{x_{40}^r}, \\ \rho_0 &= w_1 \theta_1 + w_2 \theta_2\end{aligned}\tag{10}$$

so that θ_1 measures excess in the operating base and θ_2 measures failure to turn volume into revenue. Since each stage is scored from its own slacks, a month cannot conceal a weak conversion stage behind a lean operating stage, or the reverse. The diagnostic value lies in which of the two binds, not only in the composite.

3.7. Dynamic Carry-Over Conditions

Tone and Tsutsui (2010) classify carry-over items and link successive periods through continuity conditions on the intensity vectors. That presupposes periods nested within units; here the periods are the units, so it is adapted as two contemporaneous conditions on the static programme, one on what a month inherits and one on what it leaves behind. The two stocks satisfy the accounting identity

$$c_{p,t}^{in} = c_{p,t-1}^{out}, \quad p = 1,2, \quad t = 2, \dots, 60\tag{11}$$

so the inherited position is observed but not chosen. A month opening with a depleted booking book or damaged reputation is constrained by its predecessor, and charging it for that inheritance would confuse current with past management. The carry-in therefore enters as a non-discretionary input (Banker and Morey 1986): the reference set may not draw on months that inherited a stronger position,

$$\sum_{j \in J} \lambda_j^{(1)} c_{pj}^{in} \leq c_{p0}^{in}, \quad p = 1,2\tag{12}$$

The inequality, not an equality, is correct. Requiring comparators to hold identical inherited stock would, since both stocks are continuous, collapse the reference set towards the evaluated

month and yield self-referential scores. The inequality protects against inherited advantage while leaving a workable comparison group.

The stock a month passes forward is different, being the product of current decisions. Filling the peak at the cost of next season's booking book, or holding rates at the expense of reputation, are intertemporal choices a contemporaneous model would otherwise reward. The carry-out is treated as a desirable output on the second stage,

$$\sum_{j \in J} \lambda_j^{(2)} c_{pj}^{out} \geq c_{p0}^{out}, \quad p = 1, 2 \quad (13)$$

Eq. (13) disadvantages a month that runs down its stocks. Because the first observation's carry-in is unobserved, January 2021 is excluded, leaving 59 units; Section 4.6 drops (13) to isolate the intertemporal penalty from the reference-set narrowing of (12).

3.8. Productivity Change and Temporal Stability

Productivity change is measured with the Malmquist index of Färe et al. (1994), applied to same-calendar-month pairs $m = 1, \dots, 12$ drawn from adjacent years a and b . Comparing July with July and January with January removes the seasonal component from the comparison without any filtering or adjustment, which is one of the practical advantages of the monthly design. Each annual pool holds twelve units, so the index is computed on a compact specification—inputs x_1 , x_2 , and $x_3 + x_4$, output $y_1 + y_2$ —for which twelve units exactly meet the $n \geq 3(m + s)$ requirement. The index and its decomposition are

$$MI_m = \left[\frac{D^a(x^b, y^b)}{D^a(x^a, y^a)} \times \frac{D^b(x^b, y^b)}{D^b(x^a, y^a)} \right]^{1/2} \quad (14)$$

$$EC_m = \frac{D^b(x^b, y^b)}{D^a(x^a, y^a)}, \quad TC_m = \frac{MI_m}{EC_m} \quad (15)$$

The geometric mean in (14) averages the index computed against the year- a frontier and against the year- b frontier, which avoids an arbitrary choice of base period. The catch-up term EC_m measures movement towards the contemporaneous frontier and the residual TC_m

measures movement of the frontier itself. Year-pair results are reported as geometric means over the twelve month pairs,

$$MI_{a \rightarrow b} = (\prod_{m=1}^{12} MI_m)^{1/12} \quad (16)$$

Because the annual pools sit at the discrimination threshold, the decomposition is read as indicative; the primary productivity measure is the global index of Pastor and Lovell (2005), immune to the infeasibilities that affect adjacent-period distances.

$$MI_{a \rightarrow b}^G = \frac{\theta^G(x^b, y^b)}{\theta^G(x^a, y^a)} \quad (17)$$

The two indices rest on different specifications and reference sets, so their levels are not comparable; what is informative is whether they move together, and agreement is read as evidence of robustness rather than a numerical check.

Temporal stability of the classification is examined with window analysis (Charnes et al. 1985).

Each window pools twelve consecutive months,

$$J_k = \{k, k + 1, \dots, k + w - 1\}, \quad w = 12, \quad k = 1, \dots, 49 \quad (18)$$

This yields 49 overlapping frontiers and up to twelve scores per month. The dispersion of a month's scores across those windows measures how far its classification depends on the reference set; horizon-end months, appearing in fewer windows, are diagnosed with less confidence.

3.9. Verification and Sensitivity Protocol

All programmes are solved in LINGO 19, outside the Excel workbook that holds the data, and none of the solver output is accepted without an independent check. Every radial score is rebuilt from its optimal multipliers as $u^\top y_0$ under the normalisation $v^\top x_0 = 1$, and every slacks-based score is rebuilt from its optimal slacks through (10). Reconstruction error is zero at the 10^{-6} tolerance for every unit. In addition, the optimal multiplier vector of each month is tested against all sixty months for cross-feasibility, $u^\top y_j - v^\top x_j \leq 0$ for all $j \in J$, which detects a

solution that satisfies its own constraints but violates those of another unit. A re-solve template allows any individual score to be reproduced without reference to the stored results.

The sensitivity analysis varies the two discretionary elements of the specification. Stage weights are moved to (0.3, 0.7) and (0.7, 0.3), and the good-link condition (13) is removed. Agreement between variants is measured by Spearman correlations computed on tie-corrected average ranks: for scores ρ_j , the rank of month j is

$$R_j = \#\{l : \rho_l > \rho_j\} + \frac{\#\{l : \rho_l = \rho_j\} + 1}{2} \quad (19)$$

Tied months share the mean of the positions they jointly occupy, a correction that matters because efficient units form a sizeable group and the minimum-rank convention in spreadsheet functions would inflate apparent agreement between specifications.

4. Empirical Application

4.1. Setting

The focal property, anonymised as the Hotel, is a 350-room, five-star, year-round coastal resort in the Antalya region of Türkiye, operating on a mixed half-board and all-inclusive basis with substantial banquet and congress activity and retaining a core establishment through the winter, so every month is a genuine operating decision. The window runs from January 2021 to December 2025 and spans the post-pandemic recovery, the 2022–2023 energy price shock, a revenue-management system introduced in July 2023, and a rooftop solar installation commissioned in March 2024.

Accounts follow the Uniform System of Accounts for the Lodging Industry, with monetary series in euros at monthly average exchange rates. Section 4.2 sets out the variables, the constant-price treatment of inputs, and the comparison of cost structure with published norms.

The panel is drawn from the property’s own monthly management accounts, made available on condition of anonymity. Because the records are proprietary, the property is identified only

by segment, capacity, and region. No value is simulated or imputed; the only transformations are the price deflation of Section 3.3 and harmonisation to a common chart of accounts.

4.2. Data, Variables, and Measurement

Table 2 defines the variables and their roles. Two features of the cost data determine what the scores can mean. First, each cost input carries a fixed and a variable component: a resort of this type retains a senior core establishment, a central plant, an administrative function, and contracted brand commitments through the low season, so treating cost as proportional to occupancy would erase the operating leverage a seasonal property must manage. Second, the refurbishment cycle (November–February) and the early-booking campaign (January–March) run against the season, keeping the input space from collapsing onto a single demand factor.

Inputs enter at constant prices. Nominal costs are deflated to January 2021 prices using input-specific indices: the minimum-wage steps for labour, the wholesale energy series for utilities, and a general cost index for the rest. Without this step the wage steps and the 2022–2023 energy shock would register as deteriorating technical efficiency, and the earliest year would appear spuriously efficient. Nominal series are retained for description.

Table 2. Variable Definitions and Model Roles

Code	Variable	Unit	Role
x_1	Staff cost (core establishment plus seasonal complement)	EUR, constant prices	Stage-1 input
x_2	Energy cost (electricity, gas, water)	EUR, constant prices	Stage-1 input
x_3	Other operating cost (F&B cost of sales, housekeeping–laundry, maintenance and refurbishment, administrative and general)	EUR, constant prices	Stage-1 input
z_1	Occupied room-nights	room-nights	Intermediate (link)
z_2	Covers served (accommodation and banquet)	covers	Intermediate (link)
x_4	Marketing and distribution cost (brand, contracting, OTA commission, campaigns)	EUR, constant prices	Stage-2 input
y_1	Rooms revenue	EUR	Final output
y_2	Food-and-beverage revenue	EUR	Final output
c_1	Forward-booking stock at month end	room-nights	Desirable carry-over
c_2	Online guest-review score	0–10 index	Desirable carry-over

env Provincial foreign arrivals thousand Environmental (outside DEA)

Notes: Monetary variables enter the models in EUR thousands. The carry-in of month t equals the carry-out of month $t-1$, Eq. (11), and is fully observed. Occupancy, ADR, RevPAR, and headcount are retained for description only.

Tables 3 and 4 describe the panel: Table 3 reports the distribution of the model variables and Table 4 the seasonal cycle the month-as-DMU design is built to exploit.

Table 3. Descriptive Statistics of The Model Variables

Variable	Mean	SD	Min	Max
x_1 Staff cost (€000)	382.8	73.4	253.3	523.8
x_2 Energy cost (€000)	64.4	15.8	45.9	113.7
x_3 Other operating cost (€000)	303.0	75.5	157.6	435.0
x_4 Marketing–distribution cost (€000)	74.9	19.6	44.4	125.8
z_1 Occupied room-nights (000)	6.42	2.05	3.13	9.86
z_2 Covers served (000)	36.90	10.41	16.60	52.63
y_1 Rooms revenue (€000)	747.6	478.8	179.4	1,925.4
y_2 F&B revenue (€000)	442.9	174.5	135.0	772.4
c_1 Forward-booking stock (000)	13.36	6.56	3.75	30.16
c_2 Review score (0–10)	8.54	0.10	8.22	8.71

Notes: Cost variables are stated at constant January 2021 prices. The narrower dispersion of the inputs relative to the outputs is the signature of operating leverage: fixed components damp the seasonal swing in costs while seasonal pricing amplifies it in revenue.

Table 4. Seasonal Profile: Five-Year Means by Calendar Month

Month	Occupancy	ADR (€)	Covers (000)	Fwd. bookings (000)	Headcount	Energy per occ. room-night (€)
January	0.374	71.3	21.5	10.8	206	13.81
February	0.412	73.7	21.7	13.6	213	13.33
March	0.428	77.6	33.4	15.4	216	11.80
April	0.512	86.5	35.6	18.5	231	10.11
May	0.654	106.8	44.7	23.5	258	8.70
June	0.800	131.6	43.4	20.0	286	8.75
July	0.839	157.2	46.6	16.8	293	8.92
August	0.836	163.2	47.9	11.5	293	8.86
September	0.786	139.1	42.9	7.6	283	8.96
October	0.670	105.7	45.2	6.5	262	9.18
November	0.483	78.3	35.4	7.2	226	11.41
December	0.428	77.4	24.6	8.8	216	13.34

Notes: Occupancy varies by a factor of 2.2 between August and January, headcount by only 1.4, and energy per occupied room-night runs 55 per cent higher in January. Forward bookings peak in May and trough in October.

Table 5 places the property's cost structure against published benchmarks, confirming that the fixed-cost shares, seasonal cost behaviour, and stock dynamics sit within the ranges reported for comparable resorts rather than being idiosyncratic to a single year or account.

Table 5. The Property's Cost Structure Against Industry Benchmarks

Property of the data	Value	Benchmark	Source of the benchmark
Fixed share of staff cost	53.6%	45–60%	Labour is roughly half of hotel operating expense; core establishment retained year-round
Fixed share of energy cost	49.8%	40–62%	A hotel at 50% occupancy uses about 80% of its full-occupancy energy (base loads, central plant)
Fixed share of other operating cost	37.7%	25–40%	Administrative and general lines are largely capacity-related
Fixed share of marketing cost	28.6%	20–35%	Brand and contracting fixed; OTA commission variable
Staff cost per head, winter / summer	1.07	> 1	Retained winter establishment is senior; unit cost must rise, not fall
Peak headcount per room	0.87	0.70–0.90	Turkish five-star all-inclusive resort norm
Energy per occupied room-night, winter / summer	1.53	> 1	Space heating; energy is the least seasonal operating line
Energy cost / total revenue	6.9% (mean)	4–6%, higher in shock years	Full-service hotel norm
Staff cost / total revenue	33.0%	28–36%	Full-service hotel norm
Review-score autocorrelation, AR(1)	0.91	high	Reputation is a stock, not a monthly draw
First principal component	72.2%	< 75%	Guards against a single latent demand factor driving all variables

Notes: The ledger also carries the usual accounting features: year-end accrual true-ups in December, banquet-revenue reclassification in congress months, a one-off refurbishment in November 2022, and severance accruals at each season end.

Across the sixty months every input correlates positively with every output (lowest 0.60), meeting the isotonicity requirement; the carry-over stocks correlate only weakly with the monthly flows, so they carry information the flows do not.

4.3. Radial Results: A Scale Problem, And A Discrimination Problem

Table 6 reports annual means of the four measures, and the radial pair is stark. Constant-returns efficiency averages 0.744, rising from 0.632 in 2021 to 0.827 in 2025, yet variable-returns efficiency averages 0.974 with almost no trend. Nearly the whole shortfall is therefore scale, not technique: scale efficiency averages 0.764. For a property carrying a fixed establishment through a season in which occupancy falls from 0.84 to 0.37, this reads as operating leverage rather than an artefact of method; with only about half of each cost line structurally fixed (Table 5), a residual part may still reflect discretionary decisions.

Table 6. Mean Efficiency Scores by Year

Year	CCR	BCC	SE	NSBM	DNSBM
2021	0.632	0.993	0.637	0.972	0.976
2022	0.709	0.954	0.745	0.897	0.931
2023	0.757	0.959	0.788	0.900	0.924
2024	0.796	0.981	0.809	0.938	0.980
2025	0.827	0.983	0.840	0.948	0.975
Mean	0.744	0.974	0.764	0.931	0.957

Notes: CCR and BCC are input-oriented radial scores on the global 60-month pool, Eqs. (3)–(5); SE follows Eq. (6). NSBM is the static two-stage score of Eqs. (7)–(10); DNSBM adds the carry-over conditions (12)–(13) and is defined for 59 months, so the 2021 row covers February–December.

The second problem is discrimination. Two months reach the constant-returns frontier but fifteen attain a variable-returns score of unity, so the radial model says nothing further about a quarter of the sample. Table 7 follows those fifteen through the network and dynamic models. Four fall below 0.98 in the static network model: March and April 2025 in conversion (stage-2 0.868 and 0.950 against near-unity stage-1), November 2021 in operations (0.944). The remaining eleven survive every model, most of them deep low-season months of 2021 on the frontier for want of a smaller peer, a boundary property rather than a statement about management.

Table 7. The fifteen BCC-Efficient Months Under Network and Dynamic Scrutiny

Month	CCR	SE	NSBM	NSBM θ_1	NSBM θ_2	DNSBM
2021-01	0.382	0.382	1.000	1.000	1.000	—
2021-02	0.415	0.415	1.000	1.000	1.000	1.000
2021-03	0.605	0.605	1.000	1.000	1.000	1.000
2021-04	0.601	0.601	1.000	1.000	1.000	1.000
2021-05	0.762	0.762	0.963	0.965	0.962	0.964
2021-11	0.593	0.593	0.972	0.944	1.000	1.000
2021-12	0.481	0.481	1.000	1.000	1.000	1.000
2024-04	0.820	0.820	0.982	0.994	0.970	1.000
2024-05	0.914	0.914	1.000	1.000	1.000	1.000
2024-09	0.943	0.943	0.993	0.986	1.000	1.000
2025-03	0.773	0.773	0.923	0.979	0.868	1.000
2025-04	0.863	0.863	0.975	1.000	0.950	1.000
2025-05	1.000	1.000	1.000	1.000	1.000	1.000
2025-07	0.997	0.997	1.000	1.000	1.000	1.000
2025-08	1.000	1.000	1.000	1.000	1.000	1.000

Notes: All fifteen months have $BCC = 1$. January 2021 lies outside the dynamic set because its carry-in is unobserved. The dynamic model restores efficiency to months whose static shortfall reflects an inherited position rather than current operation.

4.4. Stage Diagnosis: The Binding Stage Alternates

Panel A of Table 8 reports the stage decomposition, and its most useful result is negative. Averaged over the panel the two stages are almost indistinguishable (θ_1 0.935 against θ_2 0.927 static, 0.957 against 0.956 dynamic), so there is no standing answer to which half binds. The aggregate conceals a seasonal alternation: operations bind in twenty-eight of the sixty months, conversion in twenty-three, the remaining nine balanced. Operations bind in the shoulder and low-season months, when the fixed establishment is carried against thin volume; conversion binds at the peak, when rate and channel mix govern the top line. Figure 1 plots the overall and stage scores month by month.

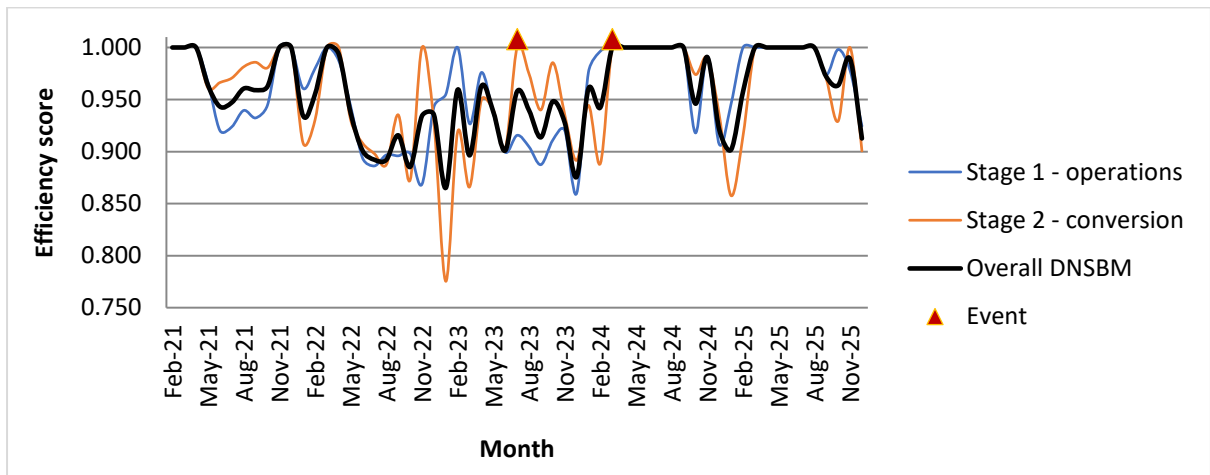


Figure 1. Monthly DNSBM Overall and Stage Scores

The dynamic constraints lift the mean by 0.027 on the fifty-nine common months, through two mechanisms Section 4.6 separates: the carry-in narrows each month's reference set, while the good-link condition penalises drawing down inherited stock and carries the substance. Each stage then responds to the shock touching it (Table 8, Panel B): θ_2 rises from 0.945 to 0.968 after the July 2023 revenue-management adoption, θ_1 from 0.942 to 0.983 after the March

2024 solar commissioning, while March 2022 scores unity despite a forward-booking stock 45 per cent below its year-later level.

Table 8. Stage Efficiencies and Event-Window Diagnostics

	NSBM θ_1	NSBM θ_2	DNSBM θ_1	DNSBM θ_2
<i>Panel A. Annual means</i>				
2021	0.958	0.986	0.966	0.986
2022	0.908	0.885	0.929	0.933
2023	0.898	0.902	0.924	0.923
2024	0.947	0.930	0.982	0.978
2025	0.963	0.934	0.985	0.964
Mean	0.935	0.927	0.957	0.956
<i>Panel B. Event windows (DNSBM, before / after)</i>				
Revenue-management system, July 2023	—	—	0.947 / 0.967	0.945 / 0.968
Solar commissioning, March 2024	—	—	0.942 / 0.983	0.945 / 0.976
Energy / revenue ratio, March 2024	—	—	0.080 / 0.046	—

Notes: Panel A covers 60 months for NSBM and 59 for DNSBM. Panel B splits the evaluated months at the event date and reports the stage score before and after each change.

4.5. Productivity Change and Temporal Stability

Figure 2 shows the Malmquist components by year pair. Productivity grows at 13.2 per cent per year pair, and the decomposition is unusually clean: technical change contributes 14.2 per cent while efficiency change contributes essentially nothing at 0.991. The frontier advances in every year pair (1.202, 1.083, 1.215, 1.076) while catch-up hovers at unity. The best months keep improving and pull the frontier while the rest of the calendar does not close the distance, locating the opportunity in the shoulder season.

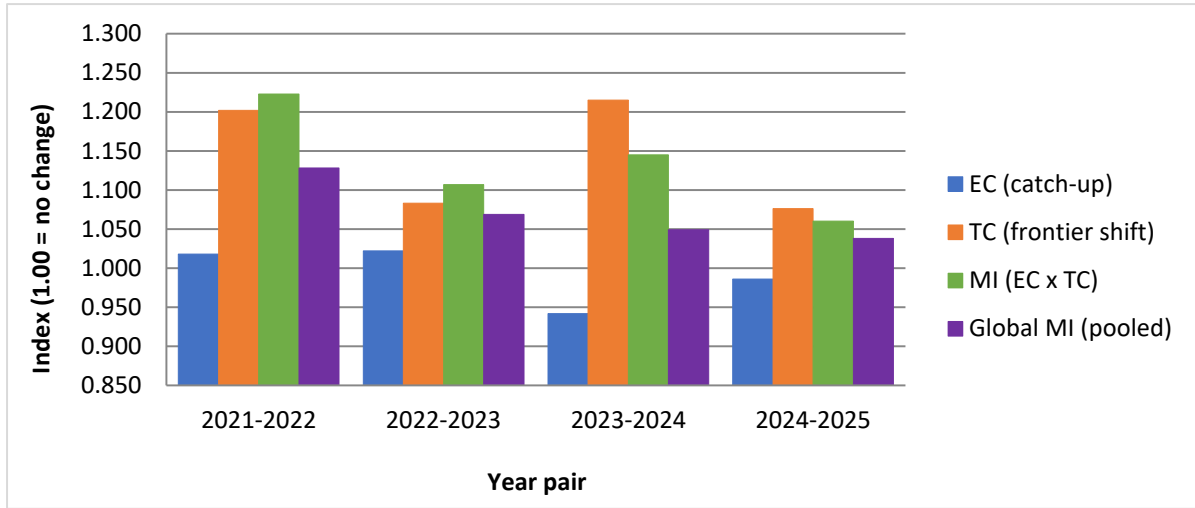


Figure 2. Malmquist Decomposition by Year Pair

4.6. Robustness

Table 9 collects the robustness evidence. Across the forty-nine twelve-month windows of Eq. (18) the mean within-month standard deviation is 0.024 and the largest range 0.216, so the classification is independent of the pooling choice (Panel A); the lower means in 2021 and 2025 are an edge effect, horizon-end months appearing in 6.5 windows against twelve, so the first and last six are read from Table 6. Figure 3 plots the mean window-DEA score by month. Shifting the stage weights to (0.3, 0.7) or (0.7, 0.3) moves the mean by a point in the third decimal and leaves the ranking intact (Spearman 0.976 and 0.980). Removing the good-link condition (13) is decisive: the mean falls only to 0.937 but the rank correlation drops to 0.758, reordering roughly a quarter of the sample. The stage weighting is immaterial while the intertemporal stock is decisive.

Table 9. Robustness of The Dynamic Network Scores

	Mean score	Spearman vs. baseline	Dispersion
<i>Panel A. Window analysis (w = 12, 49 windows)</i>			
2021 (edge)	0.667	—	0.019
2022	0.696	—	0.031
2023	0.700	—	0.025
2024	0.673	—	0.030
2025 (edge)	0.663	—	0.013

Overall	0.680	—	0.024
Panel B. Model variants (59 months)			
Baseline DNSBM, $w = (0.5, 0.5)$	0.957	—	
Stage weights $w = (0.3, 0.7)$	0.956	0.976	
Stage weights $w = (0.7, 0.3)$	0.956	0.980	
Good-link constraint (13) removed	0.937	0.758	
Static NSBM (same 59 months)	0.930	—	

Notes: Panel A dispersion is the mean within-month standard deviation across the windows in which each month appears. Panel B Spearman correlations use tie-corrected average ranks, Eq. (19). Panel A uses the compact constant-returns specification; Panel B uses the full network specification.

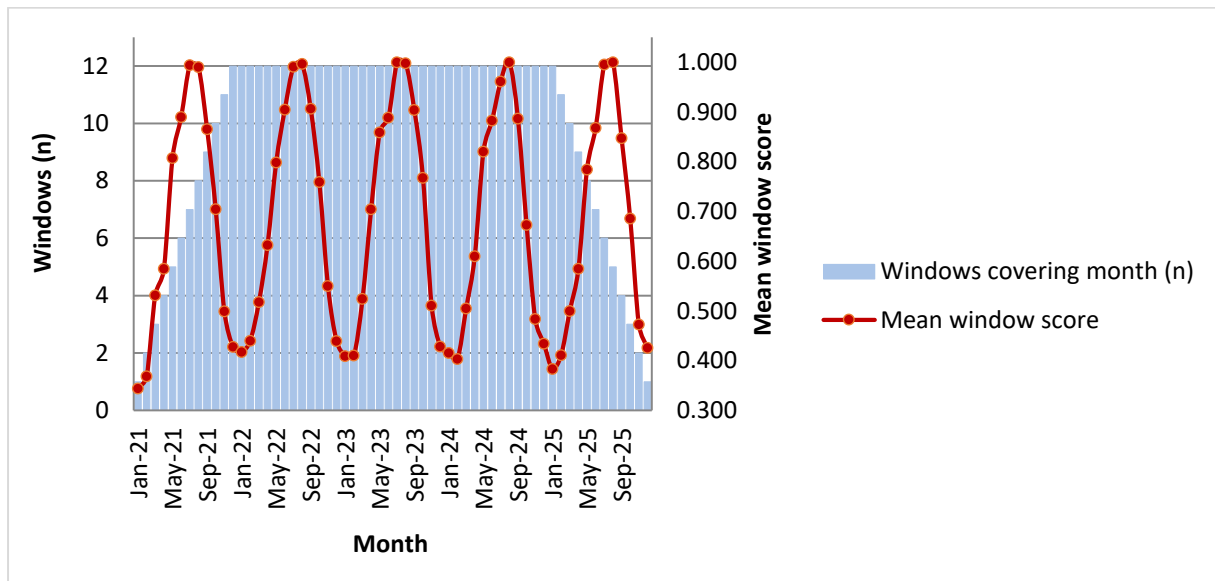


Figure 3. Mean Window-DEA Score by Month

One limitation is intrinsic to the method. Variable-returns DEA cannot discriminate at the sample boundary, so the weakest year's deepest low-season months appear efficient throughout, dominated by no smaller comparator; a longer horizon would resolve this. The Section 3.9 protocol holds: every score reproduces from its multipliers or slacks, and every multiplier vector passes the cross-feasibility test against all sixty months at 10^{-6} tolerance.

5. Conclusion

This study measured a single year-round Mediterranean resort against its own operating history. Sixty consecutive months formed the panel, each evaluated against a frontier built from the other fifty-nine: radial models established the scale of the problem, a two-stage network

measure separated the production of occupancy and covers from their conversion into revenue, and two contemporaneous conditions held each month accountable for the stocks it inherited and passed on.

Four findings follow. Almost the whole constant-returns shortfall is scale rather than technique (variable-returns efficiency 0.974 against scale efficiency 0.764); with capacity fixed at 350 rooms, this measures operating leverage carried through the low season, a gap usually inferred from margins and here read off the calendar. The two stages are indistinguishable on average, yet the binding one alternates with the season, constraining operations in the low-season months and conversion at the peak, two situations an aggregate score cannot separate.

Productivity grows at 13.2 per cent per year pair almost wholly through frontier shift, with catch-up flat (0.991): the best months keep improving and pull the frontier while the rest of the calendar does not close the distance. Removing the condition on the bequeathed stock leaves the mean almost unchanged but moves the rank correlation to 0.758 and reorders a quarter of the panel, so the intertemporal stock is where the substance lies.

These results redirect managerial attention away from the peak. Low-season months score badly on the constant-returns measure because the fixed establishment is carried against thin volume, a capacity question rather than a matter of effort. The binding stage is more actionable: the shoulder months call for staffing, maintenance scheduling, and energy management, the peak for rate strategy and channel mix. The carry-over result carries a governance implication: a month can be made to look efficient by drawing down next season's booking book or letting service strain surface later, and a system that does not price those transfers rewards it. Where Günaydın et al. (2022) called for strategies to mitigate seasonality, the monthly decomposition identifies which belongs to which month.

Three elements of the design travel beyond this application. Taking the operating month as the unit converts the homogeneity requirement of DEA from an assumption to be defended into a property of the sample, at the cost of one-asset inference. Because the framework of Tone and Tsutsui (2010, 2014) presupposes periods nested within units, it is unavailable when the periods are the units; treating the inherited stock as a non-discretionary input (Banker and Morey 1986) and the bequeathed stock as a desirable output preserves the intertemporal logic without it. Deflating each cost line by its own price index keeps scores comparable across the horizon.

The design's limitations mark the next steps. Inference is confined to a single property, the price of removing cross-firm heterogeneity by construction, and the scores are point estimates; bootstrap resampling (Simar and Wilson 1998) would attach confidence intervals. Sixty months also leave the deepest low-season months without smaller comparators. The most promising extension is a monthly panel across several comparable properties, nesting periods within units again to restore the continuity conditions while keeping seasonal resolution and separating within- and between-property inefficiency directly.

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Consent to participate Not applicable.

Consent for publication Not applicable.

Data availability The data are proprietary and were provided by the hotel operator under a confidentiality agreement; they are not publicly available but may be obtained from the corresponding author on reasonable request, subject to the operator's permission.

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