Mapping Price Competition in short-term rental Tourism Market: A Spatio-Temporal Point Process Mixture Approach

Giuseppina Lo Mascolo and Giada Lo Galbo
Department of Economics, Business and Statistics,
University of Palermo, Italy
giuseppina.lomascolo@unipa.it, giada.logalbo@unipa.it

Abstract[1]

Benchmarking is fundamentally the process of measuring an organization's performance against that of its peers, often with the goal of identifying best practices to drive improvement. It can be categorized into various types, including internal, competitive, and functional. In the hospitality industry, it is primarily defined as a comparison process where organizations evaluate their services and performance metrics against competitors, or best-in-class organizations to identify areas for improvement [1]. Price benchmarking in the hospitality industry involves evaluating an accommodation's pricing strategies against its competitors to ensure optimal position within the market, shaping its overall value proposition [2] illustrate how consumers utilize past prices or competitor rates to evaluate current offerings. This phenomenon underscores the importance of benchmarking for the industry to maintain competitive advantage, but underlines the relevance of consistency of data quality to avoid a risk of misalignment. Competitor analysis and identification of suitable benchmarking partners are tedious and complex processes, often leading to organizations being disillusioned with benchmarking programs. Further varying interpretations of pricing strategies and market conditions across destinations complicate the analysis. Motivated by this gap, this study investigates the competitive environment of short-term rental accommodations in Palermo and its surrounding province (with the exclusion of Ustica Island), focusing on booking price as competitive signal. The aim is to detect whether price-setting behaviours exhibit spatio-temporal auto-

[1]

Speaker: Giada Lo Galbo.
Area: Tourism competitiveness; Behavioral Studies in Tourism.

correlation whether different pricing micro-markets emerge in relation to geographical proximity and seasonal demand differences.

In the hospitality industry, price determination encompasses a complex interplay of factors influenced by consumer behaviour, market dynamics, and strategic responses of each organizations. In particular, accommodation prices are influenced by neighborhood attributes, including competition, accessibility, and amenities, which collectively shape the pricing strategies of hotels and short-term rentals. Travellers are willing to pay more for experiences associated with unique cultural and natural heritage. Research indicate that the recognition as a UNESCO World Heritage Site often leads to increased marketing efforts improving accessibility and tourist amenities, further elevating accommodation costs [3]. In this regard, three research questions guide the work:

RQ1: *Do accommodation prices cluster in space and time, indicating competitive proximity?*

RQ2: *Can different competitive structures be detected by classifying bookings into spatio-temporal sub processes? Can neighborhood attributes affect pricing and competition?*

RQ3: *How do clusters reflect different market segments and strategic pricing behaviour, from price-followers to price-setters?*

The dataset comprises 902 reservations recorded from AIRBNB, from January, 1 to December, 31 2024, with daily rates ranging from €$19,00$ to €$951,00$, thereby capturing the entire continuum from budget to luxury accommodation supply. Methodologically, the study applies a spatio-temporal Poisson point process mixture using R, introducing the booking price as a mark of the event. Mixture configurations with two, three and four components were fitted, and the model selection process, based on AIC, supported the adoption of four mixtures with distinct pricing and locational characteristics (Tab. 1).

Table 1: Results of the model fitting for the spatio-temporal Poisson point process mixture, with $R = 4$ selected mixtures.

r	π_r	$\boldsymbol{\theta}$		t	$\sin(t)$	$\cos(t)$	$D_s(\boldsymbol{u})$	$D_t(t)$	$D_P(\boldsymbol{u})$	$D_Z(\boldsymbol{u})$	$D_C(\boldsymbol{u})$	$D_M(\boldsymbol{u})$
		$\boldsymbol{\theta}$	**−28.75**	0.00	**−0.68**	**−0.58**	**−5.72**	−0.04	**−0.76**	**−0.30**	**0.54**	**0.75**
1	0.25	$\sigma_{\boldsymbol{\theta}}$	1.05	0.00	0.18	0.13	0.08	0.08	0.14	0.14	0.01	0.09
		p	< 0.01	0.16	< 0.01	< 0.01	< 0.01	0.23	0.05	< 0.01	< 0.01	< 0.01
		$\boldsymbol{\theta}$	**2.90**	0.00	**−0.74**	**−0.72**	**0.88**	0.06	**−0.22**	**−1.15**	**−0.10**	**1.28**
2	0.26	$\sigma_{\boldsymbol{\theta}}$	4.03	0.00	0.20	0.14	0.84	0.09	0.14	0.17	0.06	0.10
		p	< 0.01	0.50	< 0.01	< 0.01	< 0.01	0.35	< 0.01	0.04	< 0.01	< 0.01
		$\boldsymbol{\theta}$	**1.97**	0.00	**−1.64**	**−0.87**	**0.66**	**0.37**	**0.23**	**−0.95**	**−0.02**	**0.67**
3	0.31	$\sigma_{\boldsymbol{\theta}}$	0.75	0.00	0.22	0.14	0.06	0.11	0.12	0.13	0.01	0.05
		p	< 0.01	0.31	< 0.01	< 0.01	< 0.01	< 0.01	0.03	< 0.01	< 0.01	< 0.01
		$\boldsymbol{\theta}$	**−28.63**	0.00	**−1.27**	**−0.55**	**0.74**	**0.70**	**−1.67**	**0.94**	**0.56**	**0.27**
4	0.19	$\sigma_{\boldsymbol{\theta}}$	2.61	0.00	0.20	0.12	0.10	0.11	0.13	0.14	0.04	0.05
		p	< 0.01	0.31	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

The intensity functions account for special distances between bookings ($D_s(\boldsymbol{u})$), temporal proximity ($D_t(t)$), and distance from key cultural attractions of the Arabian-Norman UNESCO site, Palermo's Cathedral ($D_P(\boldsymbol{u})$), and the Zisa Castle ($D_Z(\boldsymbol{u})$), in Palermo city, Monreale's Cathedral ($D_M(\boldsymbol{u})$), and Cefalu's Cathedral ($D_C(\boldsymbol{u})$), reflecting the role of heritage assets in price differentiation within the destination. Namely, the spatio-temporal intensity function is specified as follows:

$$\lambda_{\boldsymbol{\theta}}(\boldsymbol{u}, t) = e^{\left\{\theta_0 + \theta_1 t + \theta_2 \cos\left(\frac{2\pi t}{M}\right) + \theta_3 \sin\left(\frac{2\pi t}{M}\right) + \theta_4 D_t(t) + \theta_5 D_s(\boldsymbol{u}) + \cdots \right.} \\ {}^{\left. \cdots + \theta_6 D_{\mathrm{P}}(\boldsymbol{u}) + \theta_7 D_{\mathrm{Z}}(\boldsymbol{u}) + \theta_8 D_{\mathrm{C}}(\boldsymbol{u}) + \theta_9 D_{\mathrm{M}}(\boldsymbol{u}) \right\}} \tag{1}$$

where $M = 365$ days is the seasonal period length.

A finite point process mixture X with R components is defined as their weighted sum:

$$f_{\psi}(X) = \sum_{r=1}^{R} \pi_r f_{\boldsymbol{\theta}_r}(X) \tag{2}$$

each specified through its own spatio-temporal density, under the constraint that the weights sum to one $\sum_{r=1}^{R} \pi_r = 1$.

Under complete spatio-temporal randomness, and assuming independent and identically distributed occurrences, the density function of a realization from a Poisson process, $\mathbf{x}$, within a bounded spatio temporal window, $W \times [0, T)$ of area $|W| > 0$ and length $|T| > 0$, results from the product of the densities of the individual events:

$$f_{\boldsymbol{\theta}}(\mathbf{x}) = \prod_{(\boldsymbol{u}_i, t_i) \in \mathbf{x}} f_{\boldsymbol{\theta}}(\boldsymbol{u}_i, t_i) \tag{3}$$

Under the same assumption the density of the single event, $(\boldsymbol{u}_i, t_i) \subset W \times T$, is proportional to its spatio-temporal intensity function; that is, $f_{\boldsymbol{\theta}}(\boldsymbol{u}_i, t_i) \propto \lambda_{\boldsymbol{\theta}}(\boldsymbol{u}_i, t_i)$ [5].

The spatio-temporal intensity function can be formulated in a log-linear fashion, depending on the covariates:

$$\lambda_{\boldsymbol{\theta}}(\boldsymbol{u}, t) = \exp\left\{\boldsymbol{\theta'Z(u}, t\boldsymbol{)}\right\}\varrho(\boldsymbol{u}, t), \qquad \boldsymbol{\theta} \in \boldsymbol{\Theta} \tag{4}$$

Here $\boldsymbol{\theta}$ denotes the regression parameters belonging to the parameter space $\boldsymbol{\Theta}$; $\boldsymbol{Z(u,t)}$ represents the covariates observed throughout the spatio-temporal domain; and $\varrho(\boldsymbol{u}, t)$ is an offset whose effect is known in advance and does not require additional regression parameters for the specification of the intensity. This formulation enables the separation of multiple latent sub-processes driving booking activity [4].

Finding reveal that pricing behaviour in the destination is highly stratified. The first two mixtures represents accommodations with lower and more competitive pricing, spatially concentrated in areas with high accessibility and denser availability. The third and fourth mixtures identify more exclusive supply, showing maximum prices up to €880, 00 and €961, 00, respectively, and distributed across high-value areas.

The fitted model reveals distinct temporal demand peaks across mixtures. Specifically, intensity peaks equal to 1 are estimated for the first three mixtures and 2 for the fourth mixture, occurring on April 24, and 29, May 19 and 11, for mixtures 1 through 4 respectively.

For events assigned to mixtures 1 and 2, the temporal distance from the nearest reservation has no significant impact on booking intensity. However, for mixtures 3 and 4, intensity decreases as the temporal lag increases, indicating stronger sensitivity to the timing of nearby bookings in higher-value segments.

Spatial dynamics also vary across mixtures. In the first mixture, booking intensity decreases with increasing proximity distance from the nearest accommodation. Conversely, in mixture 2, 3 and 4, spatial distance from the nearest booked accommodation increases the likelihood of booking occurrences, suggesting spatial dispersion among competing units in those clusters.

The influence of proximity to cultural attraction is likewise heterogeneous:

- Mixture 1: Booking intensity decreases with distance from Palermo Cathedral and Zisa Castle, but increases with distance from the other two heritage sites.
- Mixture 2: Booking intensity increases with distance from Monreale Cathedral, and decreases with distance from the other three attractions.

- Mixture 3: Intensity decreases as distance from Palermo Cathedral increases, but increases with distance from the remaining attractions.
- Mixture 4: Intensity increases with distance from Palermo Cathedral and Monreale Cathedral, while decreases with respect to the other two heritage sites.

The spatial distribution of booking events categorized by mixture assignment confirms these patterns (Fig. 1) corroborating the differences across mixtures in special pricing behaviour detected by the model.

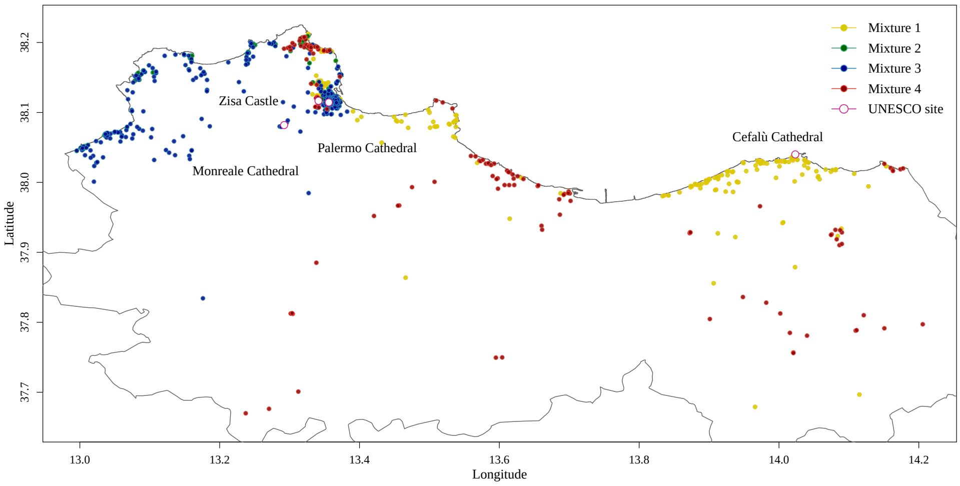
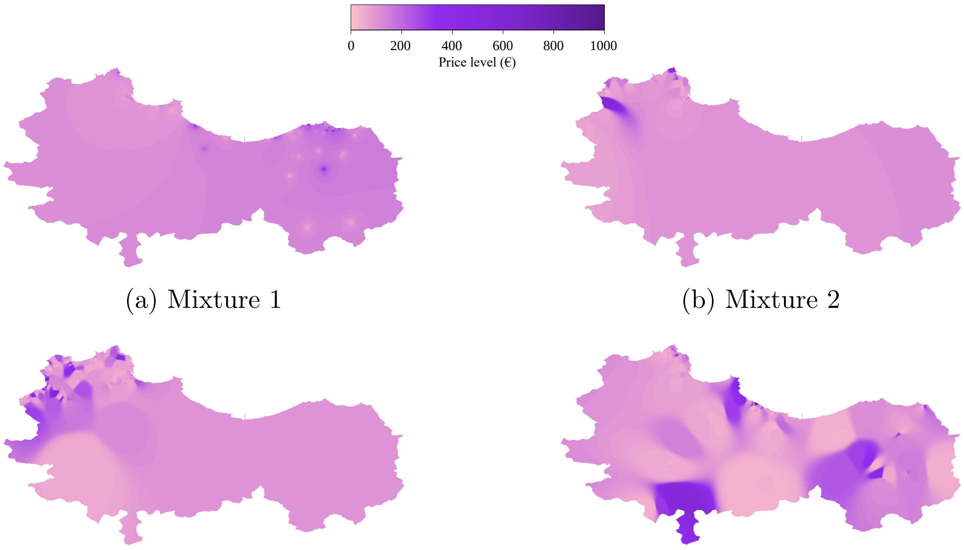


Figure 1: Spatial distribution of booking events categorized by the point process mixture, whose intensity function is defined in Eq. (1).

These differences confirm that tourism destinations internally exhibit a multi-layered market structure, where price is a function of accessibility, amenity proximity, and perceived cultural value. Autocorrelation tests indicate significant spatio-temporal dependency in pricing for mixture 1-3: when nearby accommodations increase prices, the focal property tends to adjust similarly (Fig. 2). This confirms that competition is strongest in the more affordable segments, consistent with tourism economics theory regarding price-driven rivalry in accessible markets. Conversely, the fourth mixture, identified as a premium market, shows no autocorrelation, suggesting that upscale accommodation providers display independent pricing power, behaving as price setters and competing primarily on differentiation rather than price similarity. This pattern aligns with existing evidence that unique amenities and heritage-driven attractiveness allow firms to decouple pricing from local competition dynamics.



(a) Mixture 1 (b) Mixture 2

(c) Mixture 3 (d) Mixture 4

Figure 2: Spatial surfaces of prices categorized by the point process mixture, whose intensity function is defined in Eq. (1).

From a theoretical standpoint, this research advances the integration of spatial econometrics and revenue analytics, demonstrating that competitive benchmarking should be contextualized within localized intensity patterns rather than aggregated comparisons across the entire destination. The proposed approach enables a micro-competition mapping, revealing who competes with whom, where and when, thus operationalizing competitive intelligence with a higher degree of precision. The study offers actionable guidance for hospitality managers and tourism operators. Rather than relying on category or brand affinity, competitive sets should be data-driven and location-aware, grouping accommodations that display proven pricing interdependence. This avoids benchmarking distortions that lead to suboptimal revenue decisions. Mangers in premium clusters (mixture 4) may safely pursue premiumization and value-based strategies (upselling, packaging, wellness and cultural experiences), as competitive pressure does not constrain rates. These actors can lead market repositioning.

For properties in mixture 1 to 3, where price correlation is high, pricing must respond dynamically to competitors within specific special radii and booking windows. Tactical levers include closed-to-discount strategies, early-bird incentives, and improved parity enforcement.

From the point of view of Destination Management Organization, managers can leverage these insights to balance demand dispersion, mitigate congestion in core zones, and strengthen value propositions of culturally iconic or emerging areas that drive price uplift.

Collectively, these implications indicate that price intelligence grounded in spatio-temporal modeling offers a robust foundation for destination benchmarking systems and competitive monitoring tools, enhancing fair competition and sustainable tourism value creation Palermo.

Future research should incorporate review quality, accessibility measures and environmental variable to refine the understanding the value-driven competition, as well as the co-formulation of mark density function, for the definition of the spatio-temporal marked intensity function [4]. Additionally, the model can be extended to other channel dynamics and to other accommodations, like hotel, residences and so on, improving strategy for digital distribution and price integrity across booking platform and across markets.

Keywords
Price Benchmarking; Competitive Positioning; Tourism market structure; Intensity function; Marked point pattern.

References

[1] B. Narayan, C. Rajendran, L. P. Sai, Scales to measure and benchmark service quality in tourism industry: a second-order factor approach, Benchmarking: An International Journal, **15**(2008), 469–493.

[2] G. Viglia, A. Mauri, M. Carricano, The exploration of hotel reference prices under dynamic pricing scenarios and different forms of competition, International Journal of Hospitality Management, **52**(2016), 46–55.

[3] M. Feltracco, E. Barbaro, E. Morabito, R. Zangrando, R. Piazza, C. Barbante, A. Gambaro, Assessing glyphosate in water, marine particulate matter, and sediments in the Lagoon of Venice, Environmental Science and Pollution Research, **29**(2022), 16383–16391.

[4] M. A. Taddy, A. Kottas, Mixture Modeling for Marked Poisson Processes, Bayesian Analysis, **7**(2012), 335–362.

[5] J. B. Illian, A. Penttinen, H. Stoyan, D. Stoyan, *Statistical Analysis and Modelling of Spatial Point Patterns*, John Wiley & Sons, 2008.