Seasonal Spatial Price Indices: A Case Study of Italian Accommodations

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Abstract. The diffusion of e-tourism and online booking platforms has profoundly transformed accommodation markets, generating detailed information on prices, quality, and consumer behaviour. This work analyses spatial price differentials and seasonal pricing dynamics in the accommodation markets of major Italian cities using web-scraped data. The empirical analysis is based on quarterly observations for 2024 covering 51,413 accommodation structures. To control for differences in accommodation characteristics and reputation attributes, the study employs a hedonic seasonal country–product–dummy model and an extended specification with city–seasonality interaction. The results reveal substantial heterogeneity in both spatial price levels and seasonal patterns across cities, underscoring the importance of accounting for destination-specific seasonal effects.

Keywords: Tourism economics · hedonic CPD models · seasonality · spatial price index

1 Introduction

Tourism is a rapidly expanding global industry and a significant driver of economic growth at both national and regional levels. In the European Union, the sector accounts for approximately 4.5% of gross value added, with Italy among the leading contributors and per capita tourism expenditure close to the EU average [1]. In recent years, digitalisation has profoundly transformed the tourism industry. The widespread adoption of online booking platforms and digital information has reshaped the way travellers search for, compare, and purchase accommodation, giving rise to the expansion of e-tourism. This transformation has reduced transaction costs, enhanced market accessibility, and generated big data on consumer behaviour and market dynamics [2].

Exploiting e-tourism data, this study examines spatial price differentials and seasonal pricing dynamics in the accommodation markets of Florence, Milan, Naples, Rome, and Venice, using web-scraped data from Inside Airbnb based on quarterly observations for 2024 covering 51,413 accommodations [3]. The analysis introduced two complementary econometric models. First, a hedonic seasonal

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country–product–dummy (SCPD) model is employed to estimate quality- and seasonality-adjusted spatial price indices (SPI), enabling direct comparisons of accommodation costs across cities while controlling for structural characteristics and reputation effects. Second, to capture potential heterogeneity in seasonal pricing patterns across destinations, the SCPD model is extended through a seasonal interaction CPD (SiCPD) model.

The remainder of the paper is organised as follows. Section 2 introduces the seasonal hedonic CPD models. Section 3 presents the empirical results based on the web-scraped data. Section 4 concludes.

2 Methodology

Let P_{ijt} denote the price of accommodation i located in city (or country/region) j at time t. Following the approaches in [4,5] which introduced the time CPD method and its interaction version, a hedonic SCPD model is specified as follows

$$\ln P_{ijt} = \sum_{j=1}^{J} \beta_j\, C_{ij} + \sum_{s=1}^{S} \tilde{\gamma}_s\, Q_{st} + \sum_{k=1}^{K} \alpha_k\, D_{ikt} + \sum_{m=1}^{M} \delta_m\, R_{imt} + u_{ijt}. \quad (1)$$

In Eq. (1), C_{ij} denotes a set of cities (or countries/regions) dummy variables, equal to one if accommodation i is located in city j and zero otherwise, with the associated coefficients β_j capturing quality- and seasonality-adjusted spatial price levels. Seasonal effects are captured by the dummy variables Q_{st}, which indicate whether time t falls in season s; their coefficients $\tilde{\gamma}_s$ measure the differential impact of each season on accommodation prices relative to the omitted base season. The vector D_{ikt} includes time-varying structural characteristics of accommodation i, such as the number of beds, bedrooms, bathrooms, maximum guest capacity, property or room type, and bathroom type, with coefficients α_k capturing their marginal contribution to the logarithm of prices. In addition, R_{imt} represents time-varying reputation attributes, including rating scores, number of reviews, reviews per month, and host superhost status, whose associated coefficients δ_m reflect their effect on consumers' willingness to pay. Finally, u_{ijt} is an idiosyncratic error term capturing unobserved factors.

The model is estimated with one seasonal category excluded in order to avoid the dummy-variable trap [6]. For quarterly data, the first quarter is the reference category and its coefficient is normalized to zero ($\widetilde{\gamma}_1 = 0$). Accordingly, the seasonal component can be written as $\sum_{s=1}^{S} \widetilde{\gamma}_s Q_{st} = \widetilde{\gamma}_2 Q_{2t} + \widetilde{\gamma}_3 Q_{3t} + \widetilde{\gamma}_4 Q_{4t}$, where the estimated differential seasonal coefficients are $\widetilde{\gamma}_s = \gamma_s^* - \gamma_1^*$, for $s = 1, \ldots, S$. The corresponding ideal seasonal coefficients in levels are

$$\gamma_s = \frac{\exp(\gamma_s^*)}{\bar{\gamma}}, \qquad \bar{\gamma} = \frac{1}{S} \sum_{s=1}^{S} \exp(\gamma_s^*), \qquad s = 1, \ldots, S. \quad (2)$$

By construction, the ideal seasonal coefficients satisfy property $\frac{1}{S} \sum_{s=1}^{S} \gamma_s = 1$.

The deseasonalised data are obtained as the ratio $P^d_{ijt} = P_{ijt}/\sum_{s=1}^{S} \gamma_s Q_{st}$.

The SPI [7,8] for each city j is computed as follows:

$$\mathrm{SPI}_j = 100 \times \exp\left(\beta_j - \frac{1}{J}\sum_{j=1}^{J}\beta_j\right), \tag{3}$$

where $\hat{\beta}_j$ denotes the estimated city-specific coefficient obtained from the hedonic regression and J is the total number of cities. This transformation yields price levels expressed in relative terms with respect to the average city (base = 100), thereby allowing direct comparisons of accommodation costs across cities.

The SCPD model in Eq. (1) assumes that seasonal effects are homogeneous across cities. Accommodation markets may exhibit substantial spatial heterogeneity in seasonal pricing patterns. Differences in tourism demand, local events, climatic conditions, and destination-specific attractiveness can generate city-specific seasonal price dynamics that are not adequately captured by homogeneous seasonal effects.

To account for heterogeneity, the model is extended to allow seasonal effects to vary across cities by interacting city and seasonal dummies. The resulting SiCPD model is specified as follows:

$$\begin{aligned} \ln P_{ijt} = &\sum_{j=1}^{J}\beta_j\, C_{ij} + \sum_{s=1}^{S}\tilde{\gamma}_s\, Q_{st} + \sum_{j=1}^{J}\sum_{s=1}^{S}\theta_{js}\ (C_{ij}\times Q_{st}) \\ &+ \sum_{k=1}^{K}\alpha_k\, D_{ikt} + \sum_{m=1}^{M}\delta_m\, R_{imt} + u_{ijt}, \end{aligned} \tag{4}$$

where θ_{js} captures the city-specific deviation from the common seasonal pattern in season s.

Seasonal effects are allowed to vary across cities through the inclusion of the city–season interaction terms. As a result, the overall seasonal effect for city j in season s is given by the sum of the common seasonal component and the city-specific deviation. This composite seasonal effect in logarithmic terms is

$$\gamma^*_{js} = \begin{cases} 0, & s = 1, \\ \tilde{\gamma}_s + \theta_{js}, & s = 2, \ldots, S, \end{cases} \tag{5}$$

where season $s = 1$ is the omitted reference category and is normalized to zero.

City-specific ideal seasonal coefficients (γ^*_{js}) are constructed using a procedure analogous to that of the SCPD model:

$$\gamma_{js} = \frac{\exp\left(\gamma^*_{js}\right)}{\bar{\gamma}_j}, \qquad \bar{\gamma}_j = \frac{1}{S}\sum_{s=1}^{S}\exp\left(\gamma^*_{js}\right), \qquad \text{for all } j \text{ and } s = 1, \ldots, S. \tag{6}$$

By construction, γ^*_{js} satisfy the property $\frac{1}{S}\sum_{s=1}^{S}\gamma_{js} = 1$, for all j. Deseasonalised prices are obtained by removing the estimated city-specific seasonal component from observed prices similarly to the SCPD model.

The spatial price index is further extended to allow for season-specific comparisons across cities [9]. Building on the seasonal interaction seasonal CPD model in Eq. (4), a season-specific spatial price index is constructed by combining the estimated city effects, seasonal effects, and city–season interaction terms. For each city j and season s, the index is defined as:

$$\mathrm{SPI}_{js} = 100 \times \exp\left(\beta_j + \tilde{\gamma}_s + \theta_{js} - \frac{1}{J}\sum_{k=1}^{J}(\beta_j + \tilde{\gamma}_s + \theta_{js})\right), \quad (7)$$

SPI_{js} expresses prices relative to the average city within each season (base = 100), thereby enabling direct comparisons of quality-adjusted accommodation costs across cities for a given season while keeping constant differences in accommodation characteristics and reputation attributes.

3 Results

Table 1 reports the SPI results for the SCPD model. The results reveal substantial spatial heterogeneity in prices. Venice emerges as the most expensive city, with accommodation costs 22% above the national average, followed by Florence and Rome. Milan exhibits prices close to the average, while Naples is significantly cheaper, with prices about 28% below the mean.

Table 1. Spatial price index estimated using the SCPD model.

City	Estimate	Std.Error	SPI_j
Florence	3.890	0.018	110.152
Milan	3.782	0.017	98.841
Naples	3.462	0.018	71.777
Rome	3.839	0.018	104.677
Venice	3.994	0.018	122.247

Figure 1 illustrates the SPJ_{js} derived from the SiCPD model. There is a marked heterogeneity across cities. Venice is the most expensive destination, with prices exceeding the seasonal average by more than 25% in the second and third quarters, while Florence and Rome also remain above the base level but with more moderate seasonal variation. Milan stays close to the benchmark. Naples is the least expensive city, with indices ranging from about 65–79 in the third and fourth quarters. These findings are consistent with the quarterly average accommodation prices reported in Fig. 2. In particular, the average prices for Milan and Rome closely track the overall city mean, represented by the dashed line. Venice and Florence are confirmed as the most expensive destinations, while accommodation prices in Naples remain consistently well below the city average.

The heat map of ideal city-specific seasonal coefficients in Fig. 3 confirms the heterogeneity in seasonal dynamics. Venice exhibits the strongest summer seasonality, Florence and Rome display milder but similar patterns, Milan shows weak seasonal variation, and Naples has the flattest profile overall.

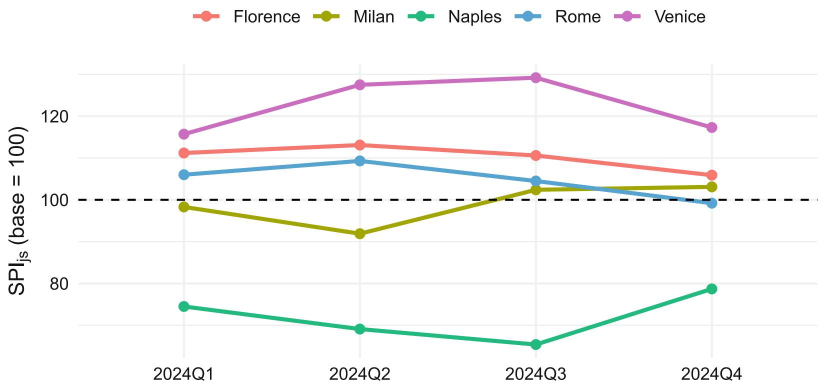

Fig. 1. Seasonal spatial price indices estimated with the SiCPD model.

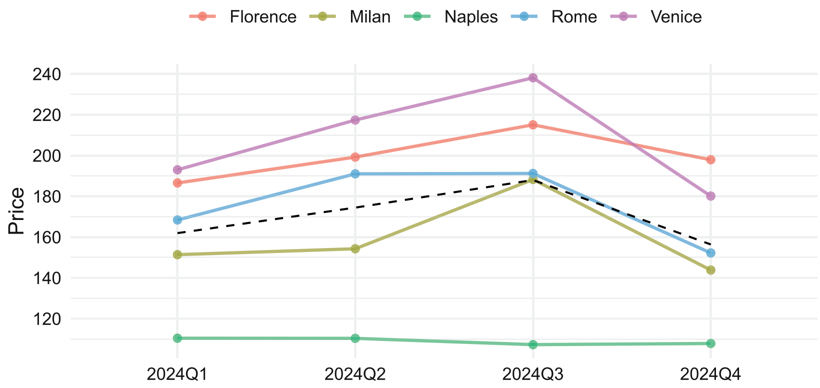

Fig. 2. Quarterly average accommodation prices by city; dashed line is the city average.

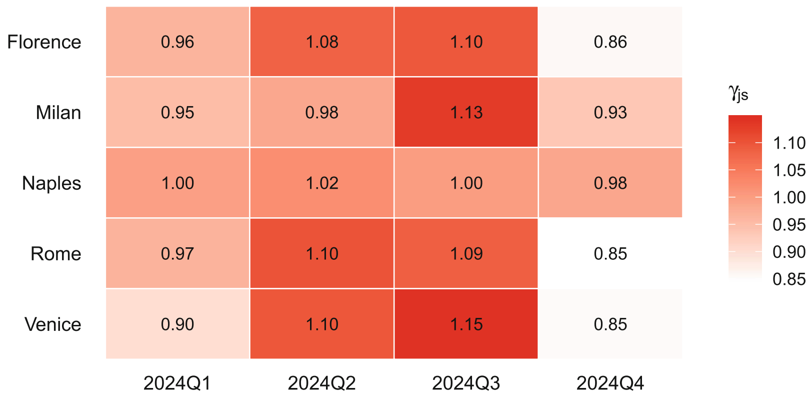

Fig. 3. Heat map of ideal seasonal coefficients estimated with the SiCPD model.

4 Conclusions

This work has examined spatial price differentials and seasonal pricing dynamics in the accommodation markets of major Italian cities. The empirical results highlight substantial heterogeneity across destinations and seasons, confirming the relevance of accounting for both spatial and seasonal effects.

Future research may extend the proposed framework in several directions. First, the model specifications could be generalised to a dynamic setting by introducing lagged price components to capture temporal dependence. Second, simulations could be conducted to assess the robustness and performance of the proposed models. Finally, the models could be applied to web-scraped hotel price data to compare pricing behaviour across different accommodation segments.

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