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Agglomeration and competition dynamic effects on hotels pricing strategies in Venice

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ABSTRACT

Many studies highlight the significance of agglomeration and spatial competition as factors influencing dynamic pricing strategies in hospitality. Our research advances the literature by examining the interaction between agglomeration benefits and competition drawback along the booking curve. To this aim, we propose a two-step Structural Vector Autoregressive (SVAR) approach that accounts for time-variant factors such as daily seasonality, room quality, and rate fences. Our findings reveal a non-linear "U-shaped" pattern of negative competition effects along the booking window, with stronger impacts observed in last-minute and very early bookings. The positive externalities associated with agglomeration increased as the advance booking period shortened. Even in times of crisis, such as during COVID-19, clustering continues to exert a slightly positive effect on rates, particularly for last-minute bookings. Overall, our research contributes to the literature on hotel revenue management and underscores the importance of integrating spatial factors into dynamic pricing models to support decision-making.

1. Introduction

Agglomeration and spatial competition are fundamental drivers of pricing strategies in the hospitality industry, as they generate both positive and negative externalities that significantly impact revenue management. This study specifically aims to clarify how these forces interact over time, by examining the balance between the benefits of agglomeration on sales prices and the challenges posed by spatial competition. We adopt a dynamic perspective that considers both advance booking and seasonality. In our view it is both useful and important to investigate how the "time effect" (i.e., the dynamics of daily online rates along the booking curve) impacts the balance between agglomeration economies and competition costs. While several studies have examined clustering and competition in the hospitality sector (See Section 2), to the best of our knowledge, no one has explored their interplay from a dynamic perspective. Our research addresses this gap providing new insights into the determinants of hotel pricing in competitive environments. In particular, it contributes to the existing literature on dynamic pricing strategies (Aubke et al., 2014), focusing on mature destinations characterized by high concentrations of tourist services. We enhance our analysis through a comparison with the COVID period, when destinations typically affected by overtourism experienced a phase of undertourism. The COVID-19 period is proposed as a unique experimental condition, a time when some positive externalities associated with clustering decreased, while price competition strategies changed in response to shifting market seasonality and booking patterns. In fact, during COVID, the high cost of property forced hotel owners to stay in the market, leading to overcapacity at tourist destinations, altering seasonality, and triggering "unhealthy" price competition strategies (Chia and Anas, 2022). The pandemic also influenced tourists' propensity to avoid risks that might lead to further cancellations, resulting in a significant shift toward last-minute bookings (Liberatore et al. 2023; Neuburger and Egger 2021). Our analysis focuses on the implications of advance booking, utilizing a robust methodology that accounts for dynamic pricing practices prevalent in the hospitality sector. We employ a two-stage analysis of a comprehensive dataset from an Online Travel Agency (OTA), modelling in the first stage the time effect by means of a Structural Vector Autoregressive (SVAR) approach. This stochastic approach aligns with modern revenue management techniques, where stochastic demand forecasting plays a key

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role in algorithmic pricing decisions (Lee, 2018) and agglomeration is shown to be a cornerstone of hotel revenue management (Huang and Zheng, 2021). Additionally, we augment our approach with exogenous variables capturing the (dynamic) effect of rate fences on daily rates. In the second stage we assess how the time-invariant price components filtered through the SVAR relate to varying levels of competitor density, thus quantifying the impact of clustering on pricing across different booking windows. This approach enables us to isolate and compare the effects of agglomeration, while providing a nuanced understanding of how market structure and booking behavior jointly influence dynamic pricing strategies across the booking curve. While acknowledging the methodological complexities of multivariate approaches, we recognize that modern dynamic pricing methods empower firms to adjust prices in real-time, similar to stock markets (Kauffman and Lee, 2010). Thus, we argue that this additional complexity is essential to capture the simultaneous effects of agglomeration and competition (Huang and Zheng, 2023). Overall, our findings are intended to guide revenue managers in integrating spatial and temporal factors into pricing decisions, as further detailed in the final remarks, and to inform both theoretical and practical approaches to revenue management in the hospitality sector. The paper is organized as follows. Section 2 provides a literature review. In Section 3, we describe the modeling framework, introducing the general formulation of our SVAR model. Section 4 illustrates the empirical investigation. In Section 5, we present the model's estimates, describing price competition patterns and discussing how positive agglomeration externalities are offset by competition density, thus revealing the underlying market dynamics. We reserve a final section to summarize the theoretical and managerial implications of our study.

2. Literature

We position our research at the intersection of studies in hospitality, geography, quantitative methods, firm behavior regarding pricing decisions and economics (e.g., Sánchez-Pérez et al. 2020, Marco-Lajara et al. 2014, Illescas-Manzano et al. 2023, Pellinen 2003, Marshall 1920), thus contributing to the literature on revenue management. While it is beyond the scope of this study to provide an exhaustive review of the literature on agglomeration, spatial competition, and dynamic pricing in the tourism and hospitality industry, this section aims to offer a concise yet comprehensive overview of the various directions researchers have explored.

2.1. *Agglomeration and price competition*

According to Marshall (1920) there are two sources of positive externalities that are generated within a destination: production enhancements and heightened demand. The latter effect is particularly significant in industries like tourism. A high degree of agglomeration is generally reached in large cities and cultural/leisure destinations, where a high concentration of companies and services guarantee a high potential demand (Papatheodorou, 2001).

Agglomeration has both positive and negative effects on operational costs and therefore on selling prices. On the negative side, it increases competition for resources. On the positive side, it can lead to a greater number of suppliers, reducing supply costs and the cost of knowledge-intensive business services (McCann and Folta, 2008), triggering tacit knowledge spillovers among hotels which are even larger for hotels with bigger competitors as peers (Bernini and Galli, 2023). Research by Marco-Lajara et al. (2014) shows that a higher concentration of tourist companies can help hotels increase profitability in terms of average occupancy. However, it can also lead to a reduction in profitability in terms of Average Daily Rate (ADR). This negative relationship between co-location and sales prices is particularly strong in popular destinations, where hotels are highly agglomerated (Arzaghi et al., 2023), even if aggressive price wars are produced by any degree of agglomeration albeit driven by substitutability among hotels (Fang et al., 2021). Many studies have examined the relationship between diversification and pricing, highlighting the importance of geographic and product attributes as mediators of this relationship. For example, Kim et al. (2020) observe positive effects on ADR for hotels located in close proximity to an airport or in densely populated locations; positive effects of the proximity to central business districts or the concentration of attractions around hotels are also reported (Lado-Sestayo et al., 2020; Sainaghi, 2011; Li et al., 2015). Regarding hotel attributes, higher-scale hotels that offer a wide range of services or belong to a chain brand enjoy greater pricing power (Becerra et al., 2013). Recently, the availability of data from OTAs has increased attention on reputation variables. Mathur (2019) finds that the increase in rates due to superior hotel reputation is greater in popular destinations where hotels are highly spatially concentrated. While several studies have explored clustering and competition in the hospitality sector, to our knowledge, none have utilized a dynamic approach to examine how these factors influence pricing strategies over different advance booking windows.

2.2. *The time effect*

Seasonality and advance booking are significant drivers of price competition. Therefore, they should be considered when the goal is to understand if the balance between agglomeration economies and competition costs changes over time (i.e., the "time effect"). Seasonality effects are particularly important in highly agglomerated areas as metropolitan cities and/or very popular destinations where events, holidays, or weekends can significantly affect daily demand. Events have a clear effect on tourists' willingness to pay higher rates resulting in significant rate increases as shown (among others) by Sainaghi and Mauri (2018) and Soler and Gémar (2017). However, the literature reports asymmetric seasonal effects based on quality differentiation (Wang et al., 2019). Lower-quality hotels often offer deeper discounts during low seasons, while high-priced hotels are generally less sensitive to demand fluctuations (Abrate et al., 2012).

In this regard, the COVID-19 pandemic has had a profound impact on pricing dynamics, significantly reducing seasonality. Moreover, during the crisis, travelers preferred option sets with no price dispersion (Giroux et al., 2022), lowering the importance of price competition even in the peer-to-peer accommodation industry as many profit-driven hosts left the market (Zhang et al., 2021). Looking at the following recovery phase, Škare et al. (2021) observe an initial rise in price competition, followed by a return to more heavy product diversification practices (e.g. re-branding or product innovation) as the pandemic caused investments to be postponed.

From a theoretical perspective, Croes and Semrad (2012) support the idea that room rates follow a stochastic dynamic process driven by seasonality (i.e., hoteliers' expectations regarding stochastic demand on different arrival days). Expanding on their suggestion, we propose that the stochastic causal chain among rates should also consider the advance booking period, as expectations for the occupancy rate on day t primarily change based on incoming bookings and cancellations.

As market competition intensifies, consumers become increasingly rational (Peng et al., 2019) and retailers may find it profitable to use price per night (Jang et al., 2019) and communication of scarcity (Teubner and Graul, 2020) during the advance booking window to attract customers. This complex combination of pricing strategies may lead to leader-follower competitive interactions (Abrate and Viglia, 2016) or to uniform pricing (Nicolini and Piga, 2019).

The booking window is also important in managing issues of price fairness and customer loyalty, which are central to price competition (Choi et al., 2017). Customers' willingness to pay for options like free cancellation and date changes becomes more valuable as the booking window expands (Masiero et al., 2020; Arenoe and van der Rest, 2020), while deal availability is crucial in decision-making processes at the last-minute (Jang et al., 2019).

We build on these insights by integrating seasonality effects with dynamic stochastic modeling, suggesting that competitive pricing strategies must account for variations in demand during peak and low seasons. We believe that this addition offer a more realistic foundation for analyzing the interplay between seasonality, advance booking, and spatial competition, advancing the existing literature.

2.3. A stochastic approach to study the advance booking effect on competition

Existing literature often treats the advance booking effect as a linear and deterministic factor, implicitly assuming a constant pick-up rate (Bigne et al., 2021). Booking time is included as a deterministic trend i.e., a variable reflecting the distance between the date of booking and the date of stay. The coefficient associated with this trend is typically highly significant, as free cancellation options incentivize hotels to set non-negative price trends to discourage consumers' speculative behaviors, such as canceling and rebooking. Alternatively, some studies focus on price competition with a fixed advance booking, indirectly assuming independence between the observed prices and previous events within the booking window (Mohammed et al., 2019; Zhao and Xia, 2020). In both cases, the influence of past stochastic peak load on intertemporal price discrimination patterns is overlooked, neglecting the active intervention of yield management strategies.

In our opinion, a more realistic and accurate description of pricing trajectories across advance bookings can be achieved by adopting a stochastic approach. This approach aligns better with dynamic pricing algorithms based on stochastic demand functions (Lee, 2018), and relational prices (Choi et al., 2017). In fact, stochastic demand functions are considered to better reflect the discrete choices made by consumers (Talluri and van Ryzin, 2005) and are also employed for joint optimization of assortment and prices by modern revenue management algorithms (Li and Talluri, 2020). Furthermore, there is a vast body of literature that emphasizes the importance of considering price trajectories throughout the advance booking period. Mohammed et al. (2021) highlight that rates change within the last-minute booking window based on the price set at the beginning of the window (a proxy for current inventory). Accordingly, Guizzardi et al. (2017) show that price trajectories exhibit a stationary AR(1) process. Abrate et al. (2019) highlight the importance of the variability and median value of prices during the advance booking period to explain how hotels compete.

Applications of Vector Autoregressive model to handle multivariate stochastic price discrimination patterns are not new in the tourism literature, although they are more commonly applied to demand forecasting rather than price modeling (Li et al., 2020; Hailemariam and Dzhumashev, 2023). One notable exception is Bergantino et al. (2018), who employ a panel-VAR model to describe price dynamics and competition in the Italian airline and railway markets, using the advance booking period as the temporal dimension, arrival dates as the cross-sectional dimension, and different companies as the multivariate dimension of the price time series. By incorporating appropriate dummy variables among the covariates, they examine competitive pricing while considering the effects of seasonality and bank holidays. In our study we attempt to address some of the methodological limitations of existing approaches in the context of highly agglomerated hotel markets. Specifically, we develop a two-stage methodology that integrates a Structural Vector Autoregressive model with exogenous variables reflecting spatial concentration, product quality and reservation conditions, allowing a more effective investigation of competitive pricing strategies while ensuring interpretability. Our approach allows us to overcome the constraints of traditional panel-VAR models, offering new insights into the dynamic relationships between advance booking, competition, and agglomeration economies.

3. Methodology

We estimate a two-stage Structural Vector Autoregressive (SVAR) model as in Guizzardi et al. (2020) to study the balance between the benefits of agglomeration and the drawbacks of spatial competition on the Best Available Rates (BARs), filtering out dynamic pricing effects. The two-stage structure of the model is motivated by the need to disentangle the temporal dynamics of price formation (first stage) from the spatial effects of competition (second stage).

First, we treat price discrimination patterns as a multivariate phenomenon, conditioning the stochastic dependence across the advance booking period on both seasonality and product quality or reservation conditions (e.g., time-variant cancellation or meal policies). We consider that the hotels are heterogeneous with respect to the propensity to apply pricing policies (e.g., Ivanov et al., 2021). Our approach accommodates the heterogeneity across hotels by estimating a separate model for each hotel. Second, we model the filtered systematic contributions of time-invariant attributes as a function of the competitor spatial density.

In the first stage, we focus on modeling $y^i_{t-j,t}$, which represents the logarithm of the BARs posted by the i-th hotel ($i = 1, \ldots, N$) at the advance booking j ($j = 0, \ldots, J$) for the arrival day t, with J being the maximum advance booking period considered. Logarithmic transformation is introduced to stabilize the variance and interpret coefficients as elasticities.

For each hotel, we specify a SVAR model for the $J \times 1$ vector $Y^i_t = \left(y^i_{t,t}, y^i_{t-1,t}, \ldots, y^i_{t-J,t}\right)'$. The model can be expressed as (we have omitted the subscript i to simply the notation):

$$Y_t = C + AY_{t-1} + \Gamma X^s_t + \Theta X^f_t + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \Sigma) \tag{1}$$

$$\eta_t = B\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, I_k), \quad BB' = \Sigma, \tag{2}$$

where X^s_t is a vector of exogenous seasonal variables, and X^f_t is a vector of room-features or rate-fences associated to the BAR offered in t. Specifically, X^s_t includes six variables capturing seasonal patterns, while X^f_t comprises four variables that account for room-specific attributes such as cancellation policies, meal options, and room quality. In this way, we augment our approach with exogenous variables reflecting the dynamics of rate fences in the booking window. The flexibility of our specification allows for variations in these vectors depending on the specific context of the hotel.

The matrices A and B are critical to the model: A captures the autoregressive structure of the BARs, while B represents the contemporaneous relationships among variables. Both A and B are constrained to be upper triangular, ensuring that causal relationships flow from lower to higher advance bookings, in line with the natural chronological ordering of time. Together, they allow us to estimate how a shock propagates through the advance booking trajectory.

The vector C is a time-invariant component that represents the pricing policy of the i-th hotel, after controlling for seasonal factors and room quality attributes. This component isolates the systematic pricing structure that is independent of time-varying influences. The estimation of the coefficients in equations (1) and (2) is performed under the assumption of Gaussian errors using constrained maximum likelihood estimation, which is asymptotically equivalent to a feasible generalized least squares estimator (Lütkepohl, 2005).

To assess how shocks propagate over time in the pricing dynamics, we compute the Impulse Response Functions (IRFs):

$$IRF_j(h) = A^h b_j, \quad h = 0, 1, \ldots, H, \quad j = 0, 1, \ldots, J \tag{3}$$

where b_j is the j-th column of the matrix of structural coefficients B, and H and J represent the maximum horizon and the maximum advance booking period, respectively. The IRFs quantify the dynamics of rates over both the advance booking period and the days following the arrival day, after a simulated rate adjustment due to unexpected bookings or cancellations, and/or a change in competitor behavior. This provides powerful insights into the expected pattern of pricing adjustments after a shock, which is a critical aspect of revenue management strategies.

In the second stage, we model the estimated time-invariant pricing component for the i-th hotel at advance booking j ($\widehat{C}_{i,j}$) obtained from the maximum likelihood estimates of the SVAR model as a function of spatial competition. Specifically, we use the following model:

$$\widehat{C}_{i,j} = \alpha_j + \beta_j Comp_i + \upsilon_{i,j}, \quad \upsilon_{i,j} \sim \mathcal{N}\left(0, \sigma_j^2\right) \tag{4}$$

where $Comp_i$ represents the weighted number of competitors for the hotel i. The competition measure $Comp_i$ is defined by the geographical proximity between hotels, with the competition probability decreasing exponentially with distance, as follows:

$$p(h_c \rightarrow h_i | d_{ci} = \lambda) = 10.95\lambda^{-0.90} \tag{5}$$

where d_{ci} is the distance between hotels h_c and h_i, and λ is a parameter governing the rate of decay. The variable $Comp_i$ is computed as:

$$Comp_i = \sum\nolimits_{c=1}^{N} p(h_c \rightarrow h_i | d_{ci} = \lambda) \mathbb{1}_{p \geq \bar{p}} \tag{6}$$

where $\mathbb{1}_{p \geq \bar{p}}$ is an indicator function that takes the value 1 if the competition probability exceeds a threshold $\bar{p}$, and 0 otherwise. Different thresholds for $\bar{p}$ can be used to assess the sensitivity of the results to changes in the definition of competition.

The estimation of the coefficients in model (4) is performed using a robust Ordinary Least Squares (OLS) estimator.

4. The empirical investigation

4.1. Data and variables

We focus on an international cultural/leisure destination where the excess of demand (overtourism) increases the complexity of the pricing mechanisms that tourism companies use to maximize product value. Venice was a destination strongly affected by COVID-19, its market is 70 % international, and therefore subject to the ban on international travel due to the pandemic, while the domestic market was also hit by government regulations on mobility.

The first ministerial act that prohibited people from any form of gathering in public places was dated March the 9^{th}, 2020 but the initial effects of the pandemic had already emerged in February 2020, as the epidemic spread to many countries. Accordingly, we identify as the starting date of the COVID period March 1^{st}, 2020, considering a pre-COVID period ranging from January 1^{st}, 2019 to February 29^{th}, 2020, with a total of 425 observations, while the COVID period runs from March 1^{st}, 2020 to June 1^{th}, 2020, including 107 observations.

We collected data on 3 advance bookings, namely $j = 0, 7, 28$, that is 2 early booking prices and a proxy for prices charged to walk-in guests ($j = 0$). With the aid of a web-scraping software we simulate a customer searching for a room at each of the above three different advance bookings. We daily scrape all the posted offers keeping the best available rate (BAR) when, based only on the characteristics observed, the rooms appear equal. This choice ensures the highest homogeneity with respect to possible (unobservable) product differentiation practices. By means of our web-scraping search, we identified 281 3/4/5 stars hotels as they more likely practice dynamic pricing strategies (Ivanov et al., 2021). We then selected the 102 most active online located on the island of Venice, 34 % of which are in the city center (within 0.5 km of Piazza San Marco), and 97 % are located within 2 km of Piazza San Marco.

Then, for each hotel i, we specify a SVAR model for the BAR offered for a stay in t, with advance booking j ($y^i_{t-j,t}$) as in (1)–(2), where the variables vectors are as follows:

$$Y_t = \begin{pmatrix} y_{t,t} \\ y_{t-7,t} \\ y_{t-28,t} \end{pmatrix}, \quad X_t^s = \begin{pmatrix} fairs_t \\ biennale_t \\ carnival_t \\ we_t \\ august_t \\ hol_t \end{pmatrix}, \quad X_t^f = \begin{pmatrix} breakfast_t \\ cancellation_t \\ items_t \\ prices_t \end{pmatrix} \tag{7}$$

The exogenous seasonal variables vector X_t^s includes the following 6 dummy variables:

- $fairs_t$, which takes value 1 in correspondence of the most visited fairs/events, where extreme price values (above the 75th percentile) occur,
- $biennale_t$, which is equal to 1 in correspondence of the Biennale,
- $carnival_t$, which is equal to 1 during the Carnival period,
- we_t, which assumes the value of 1 for Saturdays and Sundays,
- $august_t$, which is equal to 1 in August and
- hol_t, which is equal to 1 in during the holidays.

Moreover, the vector X_t^f includes the following 4 variables:

- $breakfast_t$, which is equal to 1 if the breakfast is included in the price,
- $cancellation_t$, which is equal to 1 if the room can be canceled with no penalties,
- $items_t$, which is the number of features of the offered room (air conditioning, etc…) and
- $prices_t$, which is the number of prices published by the same hotel, a proxy for the stock of available room for day t.

In order to evaluate the time series properties, for each hotel, we performed a stationarity analysis using the Dickey-Fuller test, which allowed us to determine the presence of unit roots.

Given this specification of model (1)–(2) and (4), in the next paragraph we present some descriptive statistics focusing on the pre-COVID and COVID periods.

4.2. Dynamic pricing statistics

Table 1 presents a comparison of descriptive statistics for hotel pricing before and during the COVID-19 pandemic, for the various advance bookings considered (j). As expected, the average BARs during the pandemic are lower than those before the pandemic, and the differences are more pronounced j increases. Before the pandemic, the high demand pressure (overtourism) helped to smooth the volatility pattern within the booking window. On the contrary, during the pandemic, the observed inverse relationship between the standard deviation and the

Table 1
Descriptive statistics for the variable *BAR*.

Pre COVID-19			
	$j = 0$	$j = 7$	$j = 28$
mean(BAR)	214.7	234.0	243.9
std(BAR)	243.1	247.3	241.6
10–90*perc(BAR)*	68–397	77–415	85–415
%cancellation	2.42 %	15.13 %	15.19 %
%breakfast	60.09 %	61.09 %	62.88 %
mean(#items)	22.8	22.8	22.7
During COVID-19			
	$j = 0$	$j = 7$	$j = 28$
mean(BAR)	214.6	202.2	203.3
std(BAR)	311.4	233.9	188.8
10–90*perc(BAR)*	66–354	73–353	85–341
%cancellation	14.16 %	27.13 %	27.73 %
%breakfast	58.12 %	58.68 %	59.79 %
mean(#items)	26.4	26.3	26.3

advance booking period suggests that hoteliers expect very low and flat incoming demand at higher advance bookings, with customers waiting for Government's last-minute decisions regarding mobility. The impact of a weaker pick-up curve is also evident when comparing the dynamics of the lowest and highest fares. In fact, the tenth percentile, representing the cheapest offers, remains relatively constant between the two periods, as discounted rates are limited by operating expenses. On the contrary, the 90th percentile, representing the highest BARs, undergoes a significant decrease as the advance booking period increases.

These evidences suggest that, during COVID, the competition shifts to the last-minute bookings, where hoteliers also compete on quality by selling first the most luxurious rooms, the ones that have higher fixed costs. In other words, it became challenging to differentiate the value of exclusive features such as a hotel's strategic location or a room's scenic view since they were no longer as scarce in the early booking. Policies related to price differentiation based on breakfast offerings remained largely unchanged between the two periods. On the contrary, during the COVID pandemic, the decrease in demand led to a significant increase in the percentage of refundable BARs. However, the importance of this rate fence continues to decrease as the advance booking period increases, both in the pre-pandemic and pandemic periods.

Table 2, presents some descriptive statistics for competitors' co-location measured by the variable $Comp_i$ for different values of the threshold $\overline{p}$. As expected, $Comp_i$ shows decreasing values as $\overline{p}$ increases: for $\overline{p} = 0$, we obtain an average of approximately 11 competitors, a value that decreases to 3.7 and 2.8 for $\overline{p} = 0.1$ and $\overline{p} = 0.2$, respectively. For $\overline{p} > 0.2$, $Comp_i$ stabilizes just above 2.

In addition to mean and median, we also analyze the information provided by the difference between the ninetieth and tenth percentiles, which shows that the number of non-competitors ($Comp_i = 0$) increases as $\overline{p}$ rises, becoming relevant already at $\overline{p} = 0.1$ and $\overline{p} = 0.2$, and emerging as the dominant characteristic for $\overline{p} > 0.2$.

The dynamics of the number of non-competitors ($Comp_i = 0$) and the positive skewness in $Comp_i$ imply that there might be a concentration of competitors among certain hotels, potentially indicating areas of intense competition contrasted with areas where competition is less pronounced. This asymmetry in the distribution could signify varying degrees of market saturation or strategic positioning among competitors. Finally, it's noteworthy that the variability of $Comp_i$ remains relatively stable across different values of $\overline{p}$. This suggests a consistent level of spatial competition despite changes in the threshold.

The median of $Comp_i$ decreases much faster than the mean as $\overline{p}$ increases, indicating significant positive skewness. This mirrors the high number of competitors of the hotels located in the central area of the island. The main effect of $\overline{p}$ on $Comp_i$ occurs for $\overline{p} = 0$ and $\overline{p} = 0.1$, while for $\overline{p} > 0.10$, we observe relatively similar dynamics.

5. Estimation results

5.1. Pre-COVID-19

Our first focus is on the distribution of the 102 coefficients related to the room specific variables included in the vector X_t^f, estimated by model (1)–(2). Fig. 1 shows a high variability in the estimated coefficients across various advance bookings, for the 102 hotels analyzed. This variability reflects the varying propensity of hotels to employ dynamic pricing techniques and the heterogeneity of the pricing algorithms themselves. Starting with the top-left figure and proceeding clockwise, we notice that having many rooms available on the website negatively affects the selling price, with this effect intensifying as the advance booking decreases. Offering a cancellation policy generally leads to an increase in price, especially in the last minute, although it is precisely for $j = 0$ that we observe the highest variability. This suggests that the option of cancellation is sometimes combined with significant price discounts/surcharges to boost occupancy rate and/or the ADR. Selling a room with breakfast included generally tends to increase the price. The estimated coefficients are mostly positive, although there is significant variability among hotels. Finally, the bottom-left figure indicates that the number of features offered for a room at BAR typically has a negative effect on the BAR for early bookings ($j = 28$). This effect tends to become positive as the advance booking period shortens, suggesting that less luxurious rooms are often offered for early bookings to capture more price-sensitive leisure demand with fewer constraints on location and room quality (Alderighi et al., 2016).

A key feature of our SVAR model is the ability to calculate Impulse Response Functions (IRFs) as in (3). This allows us to assess how a price shock (related to unexpected events like reservations, cancellations or a competitor action) propagates through subsequent advance bookings and arrival days. In the first row of Fig. 2 we present IRF_0, j, which shows the impact on the price set for arrival day t and the following days (along the x-axis) due to a shock equal to the standard deviation of prices simulated at the advance booking period j. For example, if t corresponds to March 30th, the second element of $IRF_{7,28}$ (shown in the last column, second row) measures the impact on the price set for March 23rd for a stay on March 30th (and the subsequent days along the x-axis). This impact results from a one-standard deviation adjustment in the price set by the hotelier on March 2nd ($j = 28$), to respond to an unexpected event observed on March 2nd. The analysis by row shows how, for all the advance bookings considered, the response is weaker as j increases thus suggesting, as expected, that a price shock has a stronger effect for closer horizons. The IRFs underscore the proficiency of hotel managers in Venice when implementing revenue management strategies. The IRFs also show persistence for 2/3 days (2,5 is exactly the average length of stay in Venice), implying the capability of hotel managers to adjust rates for the days following the shock, based on the pick-up curve.

For the sake of brevity we do not show the estimates related to the exogenous seasonal variables vector X_t^s. However, it is interesting to note that the effect of all the variables measuring seasonality follows a U-shaped pattern with respect to the advance booking period, reaching a minimum at j = 7 (one week before arrival). The only exception to this pattern is the weekend we_t, where the shape is reversed. It should be highlighted that the seasonal effect associated with weekends has the highest coefficients compared to other estimates. Additionally, it is almost always significant, meaning that the majority of revenue managers consider it as a lever to differentiate prices, probably in connection with the ease with which this period is identified on the calendar.

With model (1)–(2) we can estimate C_j, the vector 102×1 measuring the time-invariant BAR component (at the j-th advance booking). We consider this an estimation of the value the hoteliers (can) attach to their hotels, net of the seasonal factors evaluated by X_t^s and the product differentiation strategies accounted for by variables X_t^f.

The median estimates of C_j (shown in the left panel of Fig. 3) range between 2.6 and 2, 9, exhibiting a decreasing value and increasing variability as j increases. This evidence suggests that seasonality and

Table 2
Descriptive statistics for the variable *Comp*.

	$\overline{p} = 0$	$\overline{p} = 0.1$	$\overline{p} = 0.2$	$\overline{p} = 0.3$	$\overline{p} = 0.4$	$\overline{p} = 0.5$
mean(*Comp*)	10.90	3.74	2.79	2.40	2.28	2.13
median(*Comp*)	9.25	1.53	0.83	0.40	0.20	0.00
std(*Comp*)	6.74	6.28	6.11	6.08	6.05	6.03
10–90*perc*(*Comp*)	5.98–16.21	0.23–8.32	0.00–7.53	0.00–7.03	0.00–6.94	0.00–6.60

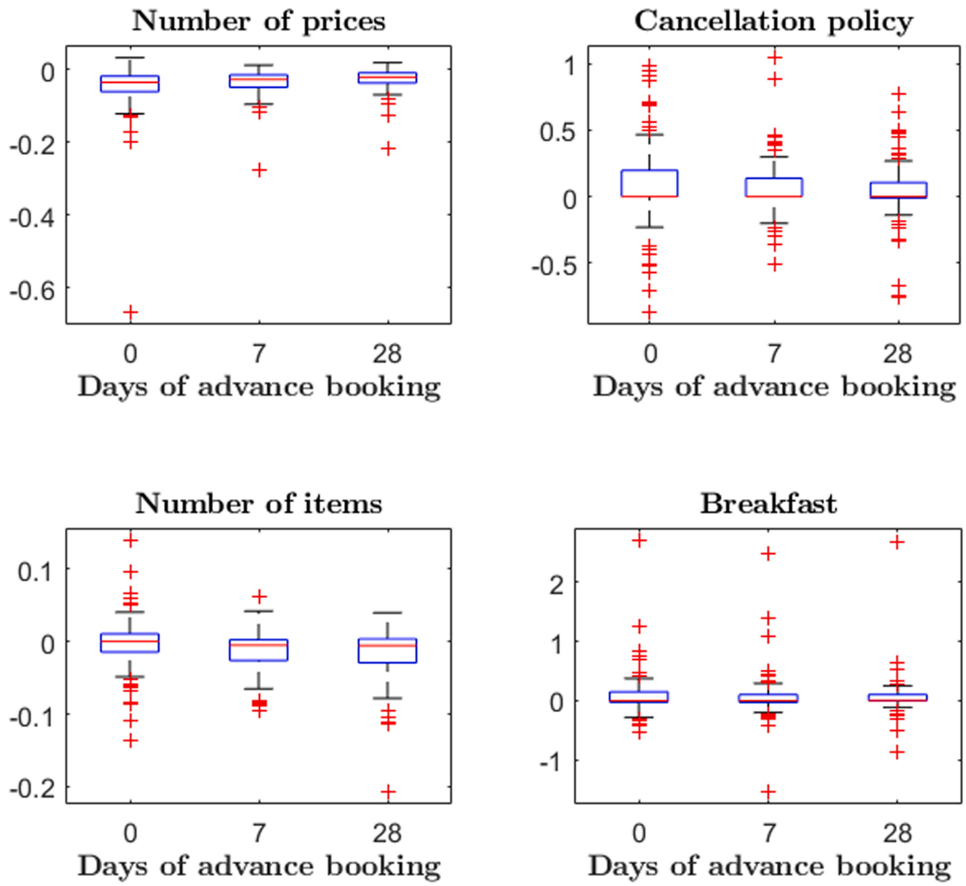

Fig. 1. Room related characteristics coefficient distributions in the pre COVID period.

price/product differentiation become more important in determining the price posted on the OTA as the advance booking period increases, and the fear of being left with unsold rooms is low. On the other hand, the price distribution in the last minute period is characterized by a thicker right tail, indicating a higher probability of extreme values for C_j. This confirms that, the price premium charged for time-invariant features, such as an exclusive location, is higher for reservations that are closer to the arrival date t. These findings are mirrored in the weight of the time-invariant features (i.e., $C_j/log(BAR_j)$) displayed in the right panel of Fig. 3. This ratio is slightly above 50 %, and decreases as the advance booking period lengthens. We also observe that peaks above 100 % are more frequent in the last-minute period, further supporting the idea that in destinations experiencing overtourism, such as Venice, it can be highly profitable to keep some rooms available for last-minute bookings in order to increase ADR.

The estimates of the relationship (4) (see Table 3), show that the effect of co-location on the rates associated with time-invariant characteristics is variable in the booking window. In particular, the parameters αs are positive and highly significant at each advance booking. They increase as the advance booking period j decreases, signaling that the value attached to the average time-invariant characteristic increases when, we expect, the room availability is low. On the other hand, the parameters βs are negative, indicating that accommodation structures struggle to differentiate themselves based on characteristics like location at any given advance booking period. Accordingly, we conclude that the negative externalities resulting from the competitive environment outweigh the positive externalities generated by the agglomeration of hotels. Furthermore, we demonstrate that hotels' ability to enhance their own time-invariant features is not constant throughout the advance booking period. In fact, the β parameters follow a "U-shaped" pattern, being higher both in the last minute and in the very early booking periods (i.e., for $j = 0$ and $j = 28$), when we expect extreme occupancy rates.

However, positive agglomeration effects can be inferred in the comparisons of the model's estimation obtained by setting different values for the parameter $\overline{p}$) (see Table 4). In fact, the β parameters decrease as the threshold value increases, suggesting the existence of positive agglomeration externalities that become more evident as the competitive effect (the weighted number of competitors) decreases. It is interesting to note that the U-shaped dynamics of the coefficients in the booking window are confirmed across different levels of competition intensity.

5.2. During COVID-19

During the COVID-19 pandemic, the increased uncertainty about the pick-up curve associated to the reduction of the arrivals had substantial implications on hotel dynamic pricing strategies. The estimated coefficients in equations (1) and (2) show strong similarities across the different advance booking periods considered (see Fig. 4). They consistently converge to an average value close to zero, indicating that few of the product differentiation strategies along the advance booking period were systematically deemed effective by revenue managers.

We report result only for the vector X_t^f, as the estimates related to vector X_t^s are even less significant. Starting with the top-left figure and moving clockwise, we observe that, in contrast to the pre-COVID period, having a larger number of rooms available on the website has a slightly positively influence on the BAR price, particularly for longer advance booking periods ($j = 28$). Therefore, offering a greater range of rooms helps maintain higher prices for rooms offered at the BAR.

The estimates associated with the effect of the cancellation policy on posted rates exhibit lower volatility compared to the pre-COVID period,

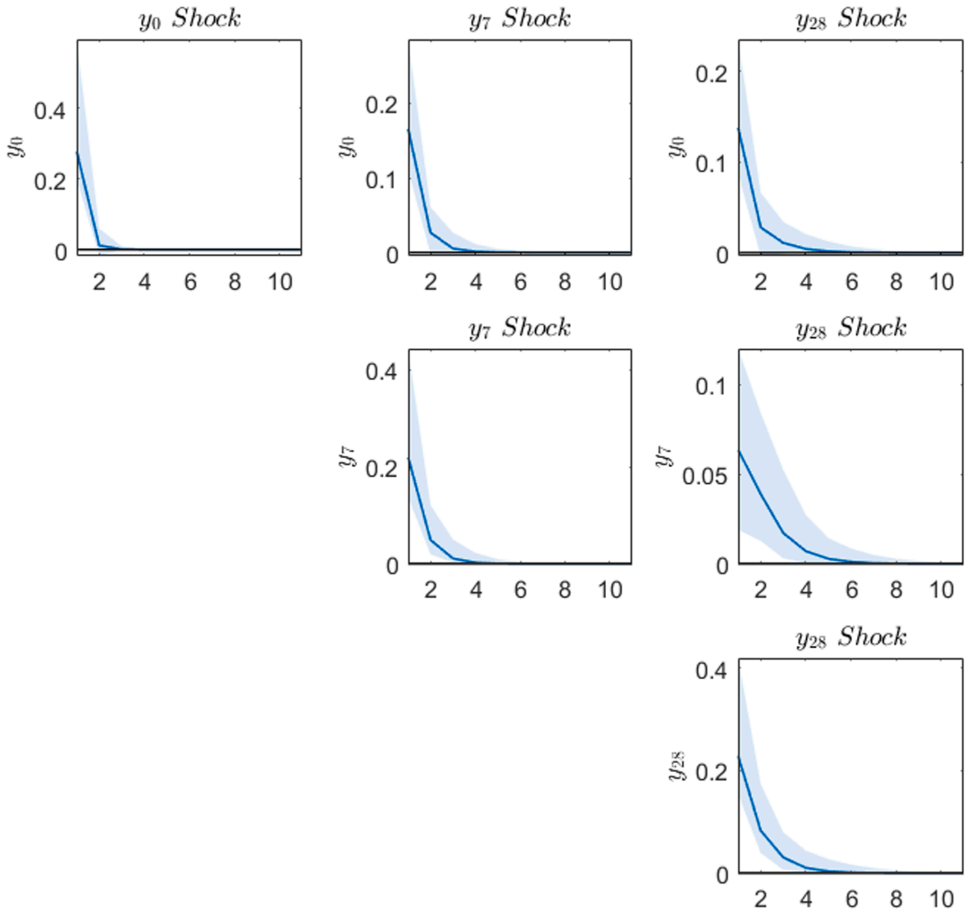

Fig. 2. IRFs in the pre COVID period.

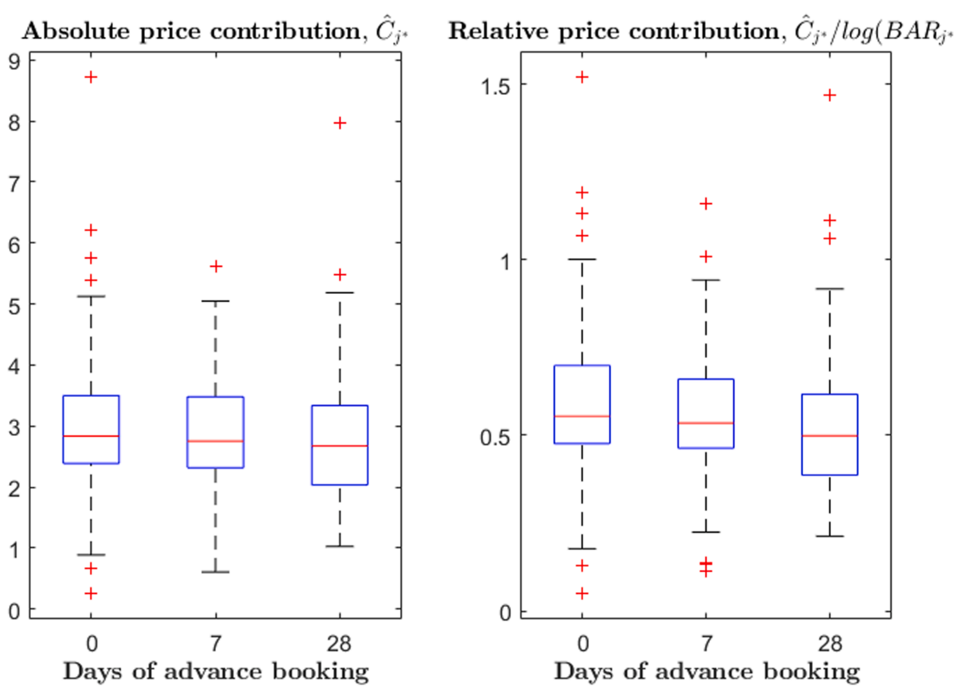

Fig. 3. Distribution of the absolute value of $\widehat{C}_j$ and the relative contribution with respect to the BAR in the pre COVID period.

Table 3
Estimates of models in (4) with $\overline{p} = 0$.

	Advance booking		
	$j^* = 0$	$j^* = 7$	$j^* = 28$
$\hat{\alpha}$	3.3781	3.0405	2.9445
	(13.2429)	(13.5761)	(11.3425)
$\hat{\beta}$	−0.0464	−0.0301	−0.0457
	(−2.3307)	(−1.7207)	(−2.2555)

t-stats in parenthesis.

Table 4
Sensitivity of $\hat{\beta}$ to different values of $\overline{p}$ in (4).

	Advance booking		
$\overline{p}$	$j^* = 0$	$j^* = 7$	$j^* = 28$
0	−0.0464	−0.0301	−0.0457
	(−2.3307)	(−1.7207)	(−2.2555)
0.1	−0.0525	−0.0364	−0.0503
	(−2.4634)	(−1.9454)	(−2.3143)
0.2	−0.0572	−0.0389	−0.0524
	(−2.6210)	(−2.0284)	(−2.3473)
0.3	−0.0588	−0.0417	−0.0542
	(−2.6879)	(−2.1678)	(−2.4230)
0.4	−0.0599	−0.0433	−0.0553
	(−2.7248)	(−2.2464)	(−2.4635)
0.5	−0.0601	−0.0443	−0.0561
	(−2.7277)	(−2.2925)	(−2.4889)

with an average value close to zero across all the considered advance booking periods. This result is expected because, amid uncertainty from mobility restrictions, few hoteliers offered non-refundable rates, as there was still an obligation to provide refunds in case of travel bans imposed by health authorities. The estimates related to the effect of the cancellation policy on posted rates show lower volatility compared to the pre-COVID period, with an average value close to zero across all advance booking periods.

This finding is anticipated because, amid uncertainty from mobility restrictions, few hoteliers offered non-refundable rates, as there was still an obligation to provide refunds in case of travel bans imposed by health authorities. Not surprisingly, selling a room with breakfast included continues to help increase the price even during the COVID-19 pandemic. Finally, the bottom-left figure indicates that, unlike the pre-pandemic period, the quality of the room offered at the best available rate consistently yields a positive effect throughout the booking period, although the variance of this effect is much higher compared to the pre-COVID period. We argue that when the demand was significantly reduced, the BAR is most affected by the total operating expenses per occupied room, and the management of price/quality ratio assumes higher importance as a competitive strategy.

Similar evidence arises from the analysis of the IRFs reported in Fig. 5, which shows much greater variability compared to the pre-COVID period (see Fig. 2). The impact of a price shock becomes more volatile, highlighting that during the COVID period (characterized by growing uncertainty regarding the future mobility restrictions) hotel managers faced greater difficulties in implementing effective revenue management strategies. The uncertainty imposed by the pandemic hindered their ability to adjust rates and dynamically respond to fluctuations in demand.

The analysis of the distribution of estimated values for C_j (see Fig. 6) confirms that prices differentiations were not based on time-invariant features during the pandemic. The box plots show a significant increase in variability, with a non-negligible number of negative values,

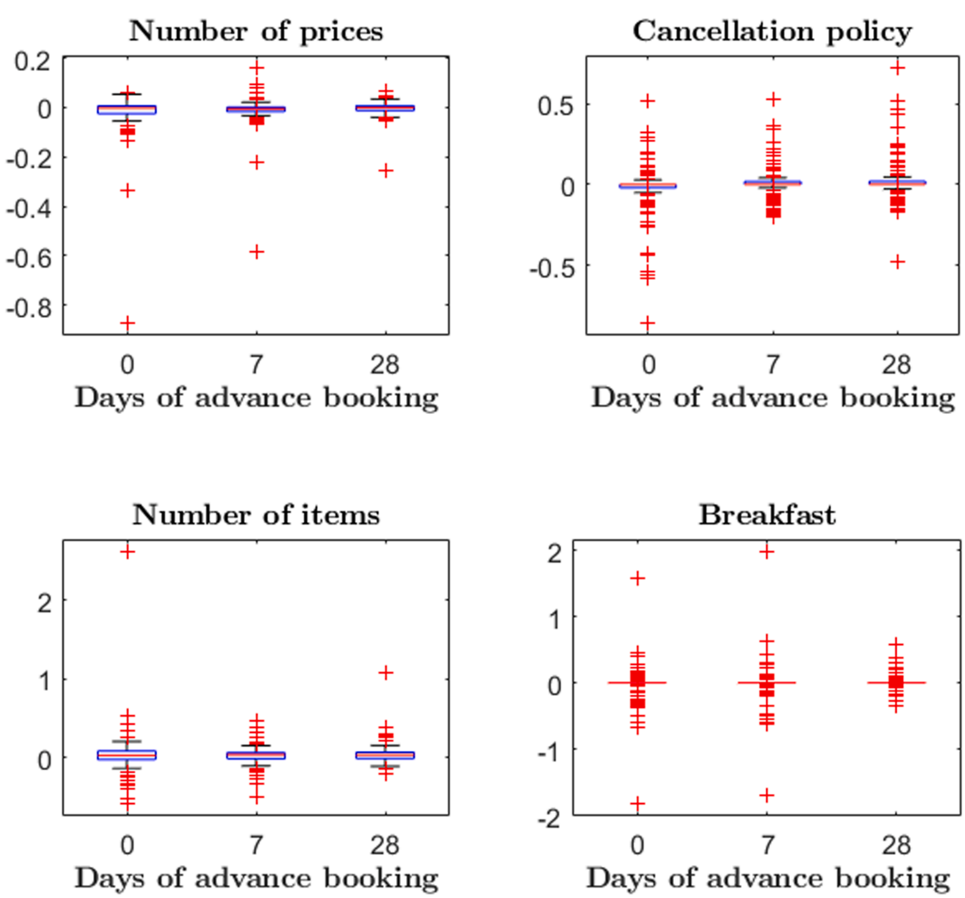

Fig. 4. Room related characteristics coefficient distributions in the COVID period.

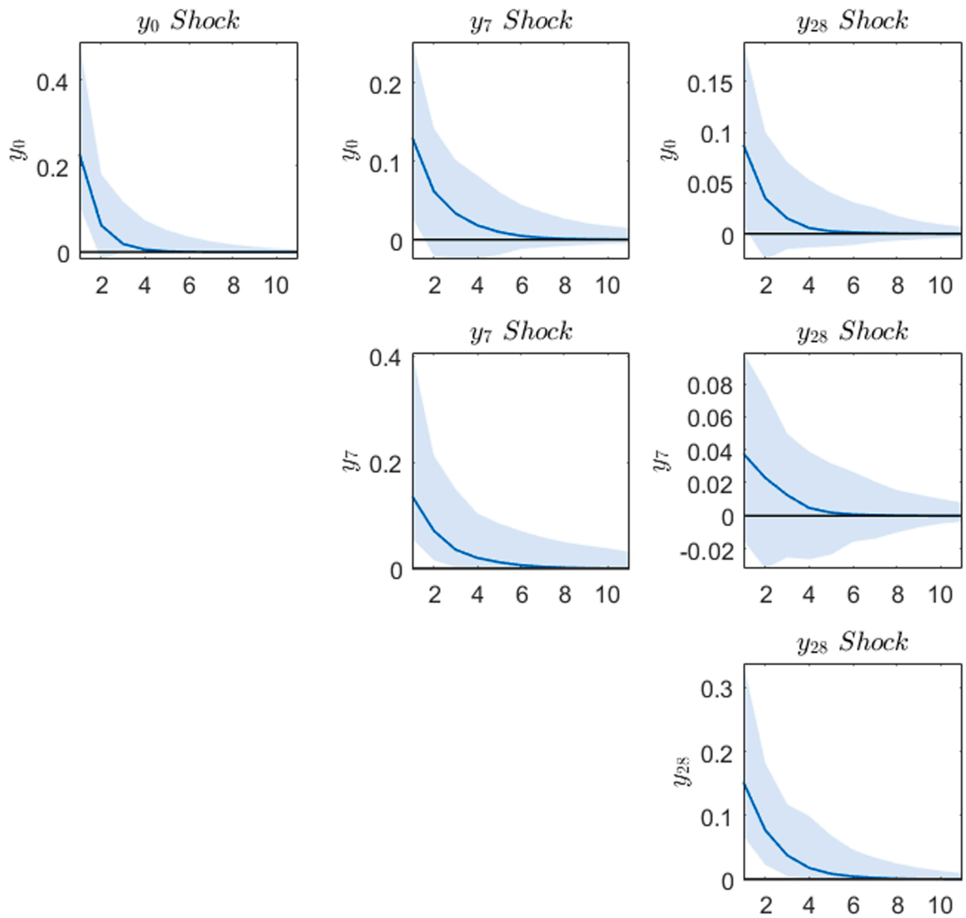

Fig. 5. IRFs in the COVID period.

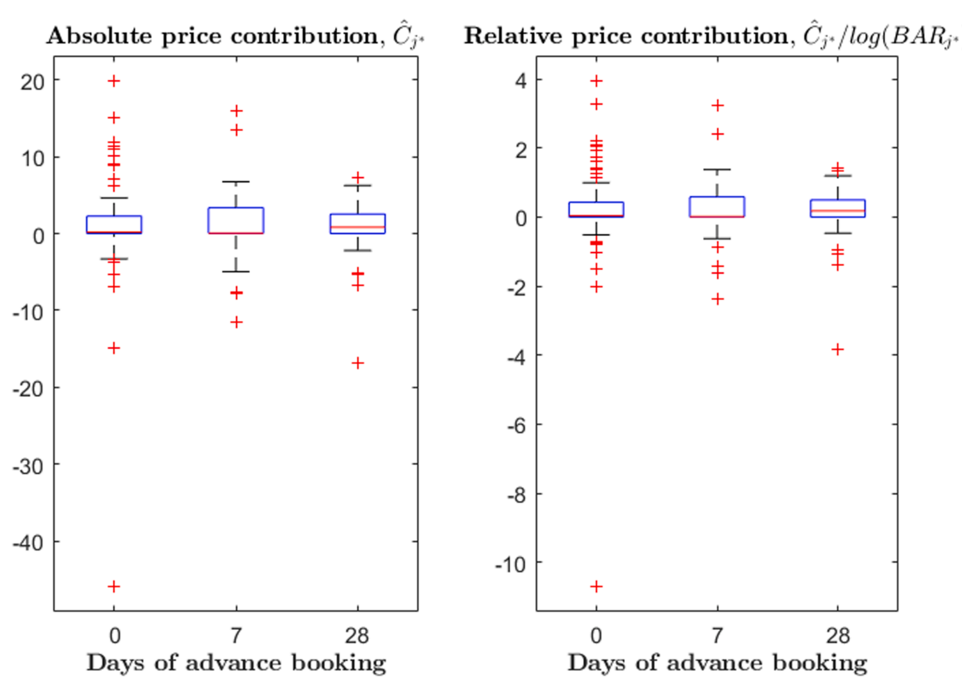

Fig. 6. Distribution of the absolute value of $\widehat{C}_j$ and the relative contribution with respect to the BAR in the COVID period.

which can be attributed to significant discounts recorded on days when demand approached zero. Although not statistically significant, this evidence is consistent with the need to increase the occupancy rate to cover fixed costs. It is not surprising that the highest frequency of extreme negative C_j is observed for advance booking $j = 0$. Fig. 6 also presents the ratio $C_j/log(BAR_j)$ (right panel), which - however - is not statistically significant due to the very low average incidence of C_j and its enormous variability.

The estimates of the α parameters of the spatial competition model, (see, Table 5) are positive and statistically significant only for early bookings. This suggests that even during the pandemic, revenue managers believed it was possible to differentiate prices based on their unique product characteristics, but only for early booking offers. The α parameter becomes insignificant in last-minute, indicating that with high unsold inventory, it becomes more important to increase occupancy rates rather than give a “right” value to the offered product. On the contrary, the effect related to competitor density completely disappears (the β parameters are never significant) for every advance booking, reinforcing the notion that the COVID pandemic has flattened price competition around total operating expenses per occupied room. Interestingly, considering different values of $\overline{p}$ (see Table 6), we observe that the β coefficients exhibit the same dynamics as the pre-COVID period. Although all the estimates are not statistically significant, the model suggests that the value to time-invariant characteristics, like location, increases with competitor density (as $\overline{p}$ decreases). Thus, positive agglomeration effects persist even during the pandemic as shown for the Airbnb listing performance in another major destination in Northern Italy by Sainaghi and Chica-Olmo (2022). However, the benefit of being located in the most touristic areas of the city (where the highest density of hotels is observed) becomes more evident as the negative (price) competition externalities weaken.

6. Final remarks

This study focuses on the effect on online rates exerted by clustering in the hospitality industry in highly concentrated tourist destinations like Venice. Unlike prior studies, which often focus on static relationships or omit market complexities, we investigate how agglomeration economies and competition costs interact at different stage of advance bookings and clustering. We analyze the prices displayed on Online Travel Agencies for the pre-COVID and during-COVID periods, leveraging the pandemic as a unique experiment, during which many factors influencing agglomeration benefits and spatial competition drawbacks were weakened. We propose a two-step approach to disentangle the temporal dynamics of price formation (first stage) from the spatial effects of clustering (second stage). In particular, we first estimate a Structural Vector Autoregressive (SVAR) model, considering the effects of seasonality, room features, and rate fences associated with the daily posted BAR. We estimate a SVAR model for each hotel, allowing for a more in-depth exploration of pricing strategies and an assessment of the value that revenue managers assign to time-invariant characteristics (such as location) across different advance booking periods. In the second stage, we model these proxies as a function of varying levels of competitor density, providing insights into the effects of hotel clustering on rates at different advance bookings and clustering intensity.

Table 5
Estimates of models in (4).

	Advance booking		
	$j^* = 0$	$j^* = 7$	$j^* = 28$
$\widehat{\alpha}$	0.6871	1.3738	1.2745
	(0.5708)	(2.1527)	(3.4673)
$\widehat{\beta}$	0.0226	−0.0283	−0.0252
	(0.2407)	(−0.5684)	(−0.8768)

t-stats in parenthesis.

Table 6
Sensitivity of $\widehat{\beta}$ to different values of $\overline{p}$ in (4).

	Advance booking		
$\overline{p}$	$j^* = 0$	$j^* = 7$	$j^* = 28$
0	0.0226	−0.0283	−0.0252
	(0.2407)	(−0.5684)	(−0.8768)
0.1	0.0107	−0.0313	−0.0246
	(0.1059)	(−0.5849)	(−0.7987)
0.2	−0.0193	−0.0354	−0.0276
	(−0.1863)	(−0.6435)	(−0.8711)
0.3	−0.0270	−0.0335	−0.0297
	(−0.2595)	(−0.6074)	(−0.9342)
0.4	−0.0278	−0.0325	−0.0303
	(−0.2658)	(−0.5853)	(−0.9500)
0.5	−0.0277	−0.0317	−0.0307
	(−0.2634)	(−0.5692)	(−0.9587)

Our findings indicate that prior to the COVID-19 pandemic, seasonality and price/product differentiation became increasingly important in determining the price posted on the OTA as the advance booking period lengthened. Conversely, the price premium for time-invariant features, such as an exclusive location, was higher for reservations made closer to the arrival date. However, the costs of competition outweighed the positive externalities typically associated with clustering, allowing us to conclude that the net effect of clustering is negative even in destinations affected by overtourism. During the pandemic, the landscape shifted significantly. The collapse in demand, combined with the need to cover operational and fixed costs, greatly reduced the dynamism of pricing. The benefits of agglomeration largely diminished, except for early bookings, and the effects of competition became negligible throughout this period. The approach to dynamic pricing became tactical (focused on last-minute bookings), and the net effect of clustering became not significant.

6.1. Empirical and managerial implications

6.1.1. Balancing competition and agglomeration effects on BAR across advance bookings

Our findings indicate that in the pre-COVID period, advance booking significantly influences the ability to leverage time-invariant features, such as location, as well as the balance between positive agglomeration effects and negative competition effects. Specifically, hoteliers were able to charge higher prices for features like location, particularly for last-minute bookings. To capitalize on this, revenue managers should consider allocating lower-quality inventory for last-minute bookings, capitalizing on overtourism. Moreover, our analysis reveals that competitors often struggle to differentiate themselves based on location, resulting in price competition that outweighs the benefits of clustering. The observed “U-shaped” pattern indicates significant negative competition effects for both last-minute and early bookings. However, as competitor density increases, the negative effects of clustering diminish, highlighting the existence of increasing agglomeration economies. This holds true for all advance bookings, suggesting that even in competitive environments, strategic positioning within a cluster can enhance revenue potential. During the COVID-19 period, hotels experienced substantial rate reductions, making it challenging to command high premiums for exclusive features. The positive effects of clustering had a slightly positive effect on BARs but only for the last-minute bookings, while the adverse impact of business concentration lessened. Consequently, the overall effect of positive and negative externalities on the online rates became not significant. Revenue managers can, therefore, harness the benefits of clustering to attract last-minute bookers, even amidst the challenges posed by reduced demand. This reinforces the importance of implementing robust quality management practices and actively monitoring booking trends to maximize occupancy during uncertain times.

6.1.2. Effects of seasonality, room features, and rate fences on BAR across advance bookings

We observe a differentiated approach among mid- to high-quality hotels in employing dynamic pricing techniques, particularly during peak tourism periods before the COVID-19 pandemic. This approach is influenced not only by seasonality but also by factors such as room availability, room quality, and rate fences. While weekends, public holidays, and major events like Carnival or the Biennale significantly impact online rates across all advance booking periods, features like room quality and cancellation policies primarily influence dynamic pricing strategies in the last minute. Furthermore, our findings indicate that the response to simulated price shocks - arising from unexpected reservations, cancellations, or competitors' actions - decreases as the booking window lengthens (when firms perceive a smaller performance gap with competitors). This aligns with the Behavioral Theory of Organizations (March and Simon, 1993).

During the mobility restrictions imposed by the COVID-19 pandemic, the importance of rate fences, particularly free cancellation options, also decreased, reflecting a strong customer preference for refundable rooms during crises and BARs were mainly determined by operating expenses per room. In periods of crisis, when demand collapses, revenue managers should prioritize quality management to enhance the customer experience at relatively low and stable prices throughout the booking curve. This approach helps manage customers' internal reference prices and booking propensity (Choi and Mattila, 2018). The primary goal should be to maximize occupancy rates while minimizing last-minute cancellations, ensuring that hotels remain competitive even in fluctuating market conditions.

6.2. Conclusions

This study has some limitations. First, it focuses on a single city and only considers the lowest price for a one-person stay. The reliance on OTA data and a convenience-sampling method means we do not account for important time-sensitive factors like occupancy rates or pricing across other channels. However, our methodology is flexible enough to include proxies for these variables in future research and can apply to other industries with fixed capacities and advance bookings, such as event ticketing or transportation.

Additionally, our approach is limited to accommodations that consistently publish online prices and requires a customized data collection process, given the lack of a comprehensive historical database of hotel rates. This limitation highlights broader issues regarding the quality and accessibility of information in the tourism sector, pointing out key challenges in effectively using big data within the industry.

Overall, we have shown that clustering and competition have an effect on pricing policies that should be studied considering the booking time dimension. We believe our findings will enhance the integration of spatial factors into revenue management practices, leading to improved decision-making. Additionally, we contribute to a deeper understanding of dynamic pricing strategies in high-density tourist areas, demonstrating how the balance between clustering benefits and competition drawbacks changes under different competitive scenarios (i.e., overtourism vs. undertourism). Therefore, we believe this research remains highly relevant as the hospitality landscape evolves. In an era marked by ongoing global challenges, our study offers timely insights into the dynamic relationship between clustering, competition and pricing in the hospitality sector.

CRediT authorship contribution statement

Andrea Guizzardi: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michele Costa:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Giovanni Angelini:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request only for scientific research purpose

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