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Does advance booking matter in hedonic pricing? A new multivariate approach.

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Abstract

We consider prices across the advance bookings as a multivariate variable, modelling the time effect by means of a structural vector autoregression (SVAR). Its unit-specific fixed effect is taken as the dependent variable in a set of hedonic regressions allowing us to estimate the marginal contribution of the (time-invariant) attributes along the price trajectory. Results from our two-step approach indicate that past occupancy rates, events, Bank holidays and seasonality differentiate pricing strategies and tactics used across advance bookings. Moreover, time-invariant services/attributes tend to increase in hedonic value as the advance booking period decreases, reducing the contribution of dynamic pricing.

1 Introduction

The complexity of tourism products is such that considering consumers' perceptions of each service attribute associated with the price is critically important in determining its relevance to a consumer's choices and preferences (Chen and Rothschild (2010)). Hedonic price analysis is the theoretical support often used to discern which, and to what extent, specific characteristics are valued by consumers (Papatheodorou et al. (2012)).
In recent years, rapid technological progress and the proliferation of online booking platforms (OTAs) have strongly affected the behaviour of both firms and consumers. The opportunity to update prices in real time, jointly with the ability to observe the online behaviours of customers and competitors, has led to new management perspectives based on the study of customers' perceptions and price dynamics (Narangajavana et al. (2014)). The overall objective is to generate an intelligence which is able to set prices that increase value for the customers, boosting the number of bookings. Thus, dynamic pricing has become both a strategic management tool to address competition and customers' perceptions and a short-term tactical tool focused on marketing (Abrate and Viglia (2016), Guizzardi et al. (2017)).

This new empirical setting is not represented in conventional (static) hedonic models, which do not consider non-attribute variables, like price dynamics, in the econometric function. Recently, the literature has recognized the importance of an augmented approach to hedonic pricing (a non-strictly hedonic approach, in the words of Abrate and Viglia (2016)), to account for both dynamic pricing and contextual variables like: rate fences, spatial density of competitors, or destination occupancy, in the hedonic formulation. However, the focus on the "time effect" is often limited to price correlation among successive arrival dates (e.g. Soler et al. (2019)) or to the effect seasonality and special events have on the consumer's perceptions of the marginal contribution of service attributes (e.g. Herrmann and Herrmann (2014)).
Advance booking (booking time) is usually included as an explicative variable, which is highly significant. This is expected because free cancellation options tend to give a non-negative trend for prices in order to avoid speculative behaviours like cancelling and rebooking. In this respect, it is worth noting that price trajectories across the advance bookings display a significant autocorrelation (i.e. they are generally well described by a stationary AR(1) process, see Guizzardi et al. (2017)).
Overall, price correlation is observed not only between successive arrival dates (seasonality), but also in advance booking trajectories. This type of complexity cannot be properly assessed simply by considering the booking lag as a covariate; understating this aspect would lead to undervaluing the role of customers' perceptions about relational prices (e.g. of internal reference prices, IRP), as described, for example, in Choi and Mattila (2018).

This paper presents a methodology to overcome the limitations of recently proposed augmented hedonic approaches, by taking dynamics into account, in the most general sense (seasonality and advance booking effects). We propose a Structural Vector AutoRegression (SVAR) incorporating advance booking as an additional dimension. Our approach treats the price trajectory as a multivariate phenomenon, allowing the interdependencies between different advance booking to be taken into account, in addition to the serial correlation in each time series. The SVAR setting also permits treating many of the tangible, reputational and contextual attributes of the service as fixed effects, whose hedonic value across advance bookings is summarized in a vector of (estimated) unit-specific means. Thus, we can assess the marginal contribution of a set of attributes in a second step, considering the fixed effects of the SVAR model as the dependent variable. These conditional prices are the hotel specific prices, at each advance booking, net of the time effect (i.e. either price interdependencies seasonality or special events) on consumers' perceptions regarding the marginal contribution of service attributes.

We consider our two-step model as a further evolution of the "not strictly" hedonic models recently proposed in the literature. This type of dynamic and multivariate approach is expected to provide higher accuracy when modelling the impact of dynamic pricing on the marginal value of service attributes. We focus on a business destination, such as Milan (Italy), where the importance of the time effect is expected to be stronger: in fact, frequent fairs and MICE events, other than the negative seasonal contribution of weekends, increase the complexity of the pricing mechanisms that tourism companies use to maximise product value.

The rest of the paper is organized as follows: Section 2 provides a review of the existing literature on empirical models of dynamic pricing including events; in Section 3, we describe the dataset and the modelling framework, introducing the general formulation of SVAR models, and discuss the techniques adopted for model selection and estimation. In Section 4, we present the estimation results and the relevant impulse response functions; in Section 5, we discuss our findings, linking them to the existing literature about dynamic pricing, reporting managerial implications, limitations and concluding remarks.

2 Review of the literature

Hedonic price analysis is an economic evaluation technique originating in Lancaster's (1966) theory of consumer demand. The hedonic model formulated by Rosen (1974) used a conventional utility-maximizing approach to derive implicit attribute prices for multi-attribute goods under conditions of perfect competition (see also Andersson et al., 2010). When combined with revealed preference methods, hedonic price theory allows to estimate the implicit price for each attribute of a multi-attribute product.

In its original formulation, the hedonic approach is a static method, considering a single price for every observation. Following Vives et al. (2018), the hotel's star rating is the most common attribute affecting price levels followed by hotel location, or distance to focal points such as a beach or the city centre. Other features found to be important are: hotel size and age, number of staff members per room or availability of parking, though the significance depends on the hotel quality (see Hung et al. (2010) and Espinet et al. (2003)). Recently, the availability of data from OTAs has increased the attention on reputation variables and specific room attributes. For example, Latinopoulos (2018) highlights the correlation between price level and seaside view on the Sithonia Peninsula (Greece), while De la Peña et al. (2016) find significant contribution from guest reviews.

Spatial effects have a substantial impact on prices. Traditional hedonic models include exogenous variables, such as the physical characteristics of the environment or the accessibility to urban amenities, to catch the so-called neighbourhood effect (Long et al. (2007)). However, they rarely consider the "adjacency effect" (Long et al. (2007)), the spatial autocorrelation and heterogeneity among competitors that could preclude the straightforward use of the hedonic pricing techniques (Zhang et al. (2011)). Adjacency is also central in studies on the role of dynamic pricing to strengthen long-term customer relationships (Narangajavana et al (2014)).

Many management studies emphasize the importance of customers' perceptions and relational prices (i.e. internal and external reference prices, fair and ethical prices, see Read et al. (2009), Choi and Mattila (2018)), while marketing studies have long considered the role of advertised reference prices, discounts and interactive prices in a bid to influence customers' purchasing behaviour (Wolk and Span (2008)). Thus, recently, scholars proposed new hedonic models characterized by a broad market-oriented approach including competitors, the general environment and a special attention to price dynamics (e.g. Abrate and Viglia (2016), Alegre and Sard (2015), Soler et al. (2019)). Short-term pricing tactics are specifically recognized as fundamental to compete (Guizzardi et.al. (2019)) maximizing revenue performance (Mauri et al. (2019)), influencing the attractiveness of products and hence both the customers' transaction-specific, cumulative satisfaction and willingness to pay (Homburg et al. (2005), Varini et al. (2002)). This is clearly shown in the "not strictly" hedonic model proposed by Abrate and Viglia (2016). Results indicate that hotels can obtain significant price premiums from their market power and from segmentation practices across advance bookings. Ignoring these elements could lead to an omitted variable bias on the estimated shadow prices in hedonic pricing models (Cotteleer et al. (2008)).

Despite this warning, the literature does not yet seem to consider explicitly that the hedonic relationship could change along the booking window, rendering any characteristic/facility more or less important to the consumer's choice. To the best of our knowledge, in the literature there is no dynamic hedonic approach in this specific sense. Advance booking (booking time) is included as an explicative variable and the time effect is sometimes understood as price correlation among successive arrival dates or – more often – as the effect of special events and seasonality in modifying the consumers' perceptions on the hedonic value of service attributes.

On price correlation, Soler et al. (2019), Soler and Gémar (2017) notice that an autoregressive component AR(1) must be added to control for autocorrelation. While aware that results for a given location may not be generalizable to other cities or regions, Soler et al. (2019) notice that the price of

the previous day is the most important explanatory variable in their hedonic model for hotel room rates in Algarve, which highlights the importance that managers place on price stability.
Herrmann and Herrmann (2014) point out the lack of studies using appropriate statistical methods to assess the relative impact of an attribute on hotel room prices during special events. They analyse the behaviour of hotel room rates in Munich during the 2012 Oktoberfest and are among the first to use daily data to measure the impact of cultural events on room rates. Their hedonic supply-and-demand pricing model shows that weekend nights have a measurable effect on room rates, and this effect is significantly changed by the presence of Oktoberfest. The distance of the hotel from the location is also an important factor; its weight changes during the event, especially for high-quality hotels. Soler and Gémar (2017) study the effects of the April Fair in Seville. They focus on seasonality, specifying two hedonic models: one with daily dummies, the other separating weekday from weekend nights, as in Herrmann and Herrmann (2014). In addition to finding that the number of stars has a positive effect on price level, while hotel size and distance have a negative effect, the authors show that weekday room rates only experience a significant increase during the Fair.
From a methodological perspective, one way to model explicitly the relative importance of each characteristic – or the consumer's marginal willingness to pay for a characteristic - across advance bookings is the two stage SVAR proposed in our work. Since the seminal work of Sims (1980) VAR models become very popular in macroeconomics. For an exhaustive description of the econometric features of SVAR see for example Amisano and Giannini (2012). Their applications are not new in the tourism literature, even if they are more often related to demand forecasting (see, among the most recent, Martins et al. (2017) and Liu et al. (2018)) than to price modelling. Among the valuable exceptions are Bergantino et al. (2018), who consider a panel-VAR model to describe price dynamics and competition in the Italian airline and railway markets, using the advance booking as the temporal dimension, the arrival dates as the cross-sectional dimension, and the different companies as the multivariate dimension of the price time series. While their setting allows for this representation due to the low number of competing companies (three airlines and two railways), the panel-VAR approach is not feasible for large cross-sectional dimensions, as is usually the case with competing hotels at a destination. Moreover, most existing packages implementing the panel-VAR approach do not allow for restrictions on the coefficient matrices to be imposed, leading to results with a difficult economic interpretation.

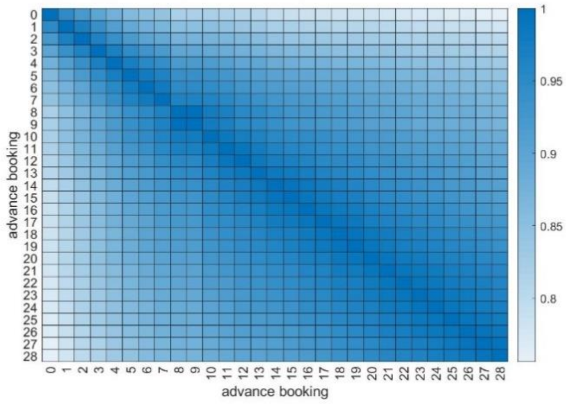
3 Data and Methods

3.1 The dataset

We construct a dataset from the Best Available Rates (BARs) published on Expedia.com every day at 00:00 AM for a panel of 107 hotels in Milan, from January 1st to September 30th 2016. We also include dummy variables to control for bank holidays, weekends and, most importantly, a selection of fairs and events between late Winter and Spring, (the periods when Milan experiences the highest occupancy rates and price changes). For each arrival date, 29 BARs were recorded, corresponding to the best price offered along a four week (from 28 to 0 days) advance booking period. The process of booking was simulated from 4th December 2015, collecting 893,664 BARs observations. The data source is Rate Tiger, a market intelligence service which monitored the pricing activity of the selected hotels (on demand and for a fee).

Fig. 1 reports the analysis of the correlation pattern between different advance bookings. The strong correlations of adjacent advance bookings demonstrate that hoteliers are attentive to consumers' IRP. The correlation allows us to reduce the dataset size by considering a subset of key advance bookings: we focus on prices at lags 0, 1, 2 for a closer look at last-minute fares, and on prices at lags 7, 14, 28 to include information regarding the medium and the long-term.

Figure 1 Correlation among BARs at different advance bookings.



The statistics in Table 2 show that the sampled hotels are primarily 4-star establishments, including one 5-star and fifteen 3-star hotels. While 54% of these hotels are independent, the remaining 46% are affiliated with a chain or franchise. They are mainly located in the city centre (75% are less than 3 km from the city centre) and they are mostly business hotels specialized in hosting MICE events. The hotels have an average of 110 rooms, much higher than the Italian national average. They offer online average BARs which increase as the advance booking period decreases. The variability of the proposed rates shows the same relationship with an important exception at advance booking 0, when it decreases considerably, signalling the hotels' propensity to "freeze" the online price at the very last minute (when cancelling and rebooking becomes impossible), thereby maintaining the (high) rates set the previous day.

Table 1: Descriptive statistics.

		median	mean	st. dev.	interq. range
Continuous/discrete variables					
BARs at adv. booking 0		114.8	135.3	89.3	(89.1;150.0)
BARs at adv. booking 1		115.0	139.0	114.1	(89.0;153.2)
BARs at adv. booking 2		113.4	137.4	106.5	(89.0;153.0)
BARs at adv. booking 7		110.5	131.8	95.1	(85.3;149.0)
BARs at adv. booking 14		110.0	129.7	88.0	(86.5;145.1)
BARs at adv. booking 28		112.5	130.5	76.3	(89.0;149.0)
# rooms	***(nrooms)***	89	110	65.2	(65;143)
# meeting rooms	***(nmr)***	2	3.3	4.3	(0;5)
# restaurant seats	***(nrs)***	0	56.2	72.2	(0;100)
distance from city centre (km)	***(dist)***	1	2.6	4.9	(0;3)
distance from airport (km)	***(dista)***	6	8.9	11.1	(0;10)

Dummy variables (hotel)		frequency	**Dummy variab. (seasonality)**		frequency
If is a 3 stars	(***3stars***)=*1*	14%	If August	(***aug***)=*1*	11%
If not affiliated to a chain/franchise	(***nochain***)=*1*	54%	If Fry. Sat. or Sun.	(***weekend***)=*1*	43%
			If Bank holiday	(***hol***)=*1*	5%
			If main Fairs/Events	(***fairs***)=1	16%

The f*airs* dummy variable assumes value 1 in correspondence of the most visited fairs/events, where extreme price values (above the 75th percentile) occur. We consider the following periods (fairs): February 14th -16th, (theMICAM, Mipel; February 23rd-28th, (Lineapelle, Simac Tanning-Tech, Myplant & Garden, Super, Mido, Mipap); March 14th-17th (Expocomfort); April 11th-16th (Eurocucina e Salone Internazionale: del Bagno, del Mobile e del Complemento d'Arredo).

Our empirical analysis has a limit in the fact that we focus on the characteristics of the hotel without exploring the characteristics of the room sold at the BAR. However, the proposed rooms are similar, as they are mainly double rooms, with double occupancy and one overnight stay. Positive neighbourhood amenities are rarely indicated (less than 2%), while internal building and room features are mentioned in association with the price at a frequency around 11%. The percentage of special offers is negligible, and a refund is guaranteed for almost all the rooms.

3.2 A two-stage hedonic model

In this Section we describe the two-stage hedonic model. At Stage 1 we consider the price trajectory as a multivariate endogenous variable in a hotel-specific SVAR model. This way, we accommodate the price evolution across time and advance booking along with many of the tangible, reputation and contextual attributes of the service as fixed effects (a unit-specific price), with a value estimated by the unit-specific mean. At Stage 2 we estimate a hedonic model considering the fixed effects obtained at Stage 1 as the dependent variable. With this two-stage approach we first control for dynamics across time and advance booking, then we use the estimated conditional prices in Stage 2 to measure the marginal contribution of a selection of hotel characteristics at different advance bookings.

Stage 1. Modelling time-based pricing via structural vector autoregression (SVAR)

Let $i = 1,2,\dots,107$ index the hotel, $t = 1,2,\dots,274$ the arrival date and $j^* = \{0, 1, 2, 7, 14, 28\}$ the number of days of advance booking. Fixing the arrival date t and the hotel i, we obtain a price trajectory constituted, in our case, by a vector of six values. Thus, for each hotel i, the dependent variable consists of a six-dimensional time series for 274 arrival dates. More formally, let $Y^i_{t-j^*,t}$ be a $p = 6 \times 1$ vector of natural logarithm of the BARs for hotel i available online for an arrival date t (second subscript) in $t - j^*$ (first subscript), i.e. at advance booking j^*, C^i the $p = 6 \times 1$ vector of fixed effect and $\mathrm{X_t}$ be a $l = 4 \times 1$ vector of dummy variables taking value 1 if the arrival date t is: in August (aug_t), on a Friday, Saturday or Sunday ($weekend_t$), on a Bank holiday (hol_t) or in a fair period ($fairs_t$). Finally, ε_t is the vector of structural shocks (for more details see Amisano and Giannini (2012)). In our framework a shock could be caused by a new (unexpected) booking/cancellation.
We consider the natural logarithm of price as is customary in hedonic models (see Wooldridge, 2015). The SVAR model for the BARs of each hotel has the following representation (we drop the hotel superscript i for lighter notation):

$$Y_{t-j^*,t} = C + AY_{t-j^*-1,t-1} + \Gamma \mathrm{X_t} + B\varepsilon_t, \qquad \varepsilon_t \sim WN\left(0_{p\times 1}, I_p\right), \quad t = 1,\dots,274 \tag{1}$$

$$\xi_t = B\varepsilon_t, \qquad \xi_t \sim WN\left(0_{p\times 1}, \Sigma\right), \qquad \Sigma = BB' \tag{2}$$

where:

$$\underset{p\times 1}{Y_{t-j^*,t}} = \begin{pmatrix} y_{t-0,t} \\ y_{t-1,t} \\ y_{t-2,t} \\ y_{t-7,t} \\ y_{t-14,t} \\ y_{t-28,t} \end{pmatrix}, \quad \underset{l\times 1}{X_t} = \begin{pmatrix} aug_t \\ weekend_t \\ hol_t \\ fairs_t \end{pmatrix}, \quad \underset{p\times 1}{\varepsilon_t} = \begin{pmatrix} \varepsilon_{0,t} \\ \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{7,t} \\ \varepsilon_{14,t} \\ \varepsilon_{28,t} \end{pmatrix}, \quad \underset{p\times 1}{C} = \begin{pmatrix} c_0 \\ c_1 \\ c_2 \\ c_7 \\ c_{14} \\ c_{28} \end{pmatrix},$$

A and B are $p \times p$ matrices, and Γ is a $p \times l$ matrix. A contains the autoregressive reduced form coefficients to account for correlation effects between the price trajectories corresponding to consecutive arrival dates. B is the on-impact structural coefficient matrix, which captures the effect of a shock (e.g. the price increase/reduction caused by a new booking/cancellation) on BARs at subsequent different advance bookings (for the same arrival date). Γ contains the slope parameters $\beta_{j^*}, \gamma_{j^*}, \delta_{j^*}$ and κ_{j^*} related to the exogenous variables.

Both A and B are constrained to be upper triangular matrices, so all terms below the main diagonal are restricted to 0. This allows us to assume that significant statistical relationships can be inferred only from larger to smaller advance bookings, coherent with the chronological ordering of the endogenous variables. The estimation of the coefficients in model (1)-(2) is performed under the assumption of Gaussian errors via constrained maximum likelihood, which is asymptotically equivalent to a feasible generalised least squares estimator (see Lütkepohl (2005)). We choose this methodology over the standard OLS estimator because the latter is not efficient if A is not full, as in our setup.

In order to assess how a one-standard deviation shock $\varepsilon_{(t-j),t}$ propagate both along the price trajectory and between subsequent arrival dates, we compute the Impulse Response Functions (IRFs). IRFs displaying the dynamic response of $Y_{t-j^*,t}$ to the shock for the advance booking $j = \{0, 1, 2, 7, 14, 28\}$:

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

where b_j is the j-th column of the matrix of structural coefficients B and $H = 10$ is the maximum horizon considered, i.e. the number of days after the arrival date *t* for which we evaluate the impact of a shock. The result is a $p \times p$ table of *IRFs* with horizon H, where only the upper $p + p(p-1)/2$ are non-trivial, while the lower $p(p-1)/2$ are identically zero. In particular, $IRF_{j^*,j}(h)$ – with $j^* \leq j$ – is the response of $y_{(t+h-j^*),t+h}$ to $\varepsilon_{(t-j),t}$.

Stage 2. Modelling hedonic pricing via static regression

At this stage we assume that, for each advance booking j^*, the estimated fixed effect $\hat{C}_{j^*}$ can be decomposed into the sum of the implicit prices of the hotel's time-invariant characteristics. The implied hedonic model is specified as follows:

$$\hat{C}_{j^*} = \theta_{0,j^*} + \theta_{1,j^*}nmr \;\; + \theta_{2,j^*}nochain \;\; + \theta_{3,j^*}nrooms \;\; + \; \theta_{4,j^*}dist \;\; + \theta_{5,j^*}dista \;\; + \; + \theta_{6,j^*}nrs \;\; + \theta_{7,j^*}3stars \;\; + u_{j^*} \tag{4}$$

$$u_{j^*} \sim N(0, \sigma^2) \qquad\qquad j^* = \{0, 1, 2, 7, 14, 28\} \tag{5}$$

where $\hat{C}_{j^*}$ is a $107x1$ vector of the constants $c^i_{j^*}$ estimated in (1)-(2). Independent variables are described in Table 1. The estimation of the coefficients in model (4) under the assumption in (5), is performed with a standard OLS estimator.

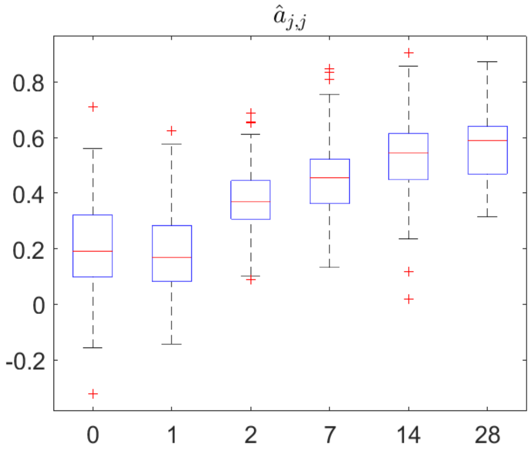
With the system (4)-(5) we are able to evaluate the marginal value that consumers hold for service attributes, net of the hotel managers' actions accounting for seasonal demand patterns and exogenous demand shocks across the advance bookings. In particular, $\hat{C}_{j^*}$ represents a price fixed effect accounting for all the time-invariant characteristics of the service, once we have controlled for the dynamic across time and advance bookings (as in model (1)-(2)).

4 Modelling price dynamics

We estimate 107 models (1), obtaining 107 matrices A, B and Γ. The autoregressive (A) and structural (B) coefficient matrices account respectively for autocorrelation between the price trajectories corresponding to consecutive arrival dates and for the effect of a shock on the BAR for a given advance booking.

In Figure 2 we report the scatter plots of the estimated $a_{i_{j^*,j}}$, which is the autocorrelation coefficient at lag 1 for hotel i and advance booking $j = j^*$.
The correlation decreases significantly across the advance bookings, reaching minimum values for $j \leq 1$, where price trajectories show null and sometimes negative autocorrelations (i.e. dynamics oscillating around an average price). This indicates that pricing tactics are more important than pricing strategy at shorter advance bookings, stemming from the need to compensate for last minute decreases in the occupancy rate when faced with unpredictable events, such as cancellations. Symmetrically, strategy acquires importance at higher advance bookings, as the hoteliers aim at maintaining non-decreasing prices trajectories with as a low variance as possible, in order to prevent speculative customer behaviours (like cancelling and rebooking) and to address the customer's internal reference price.

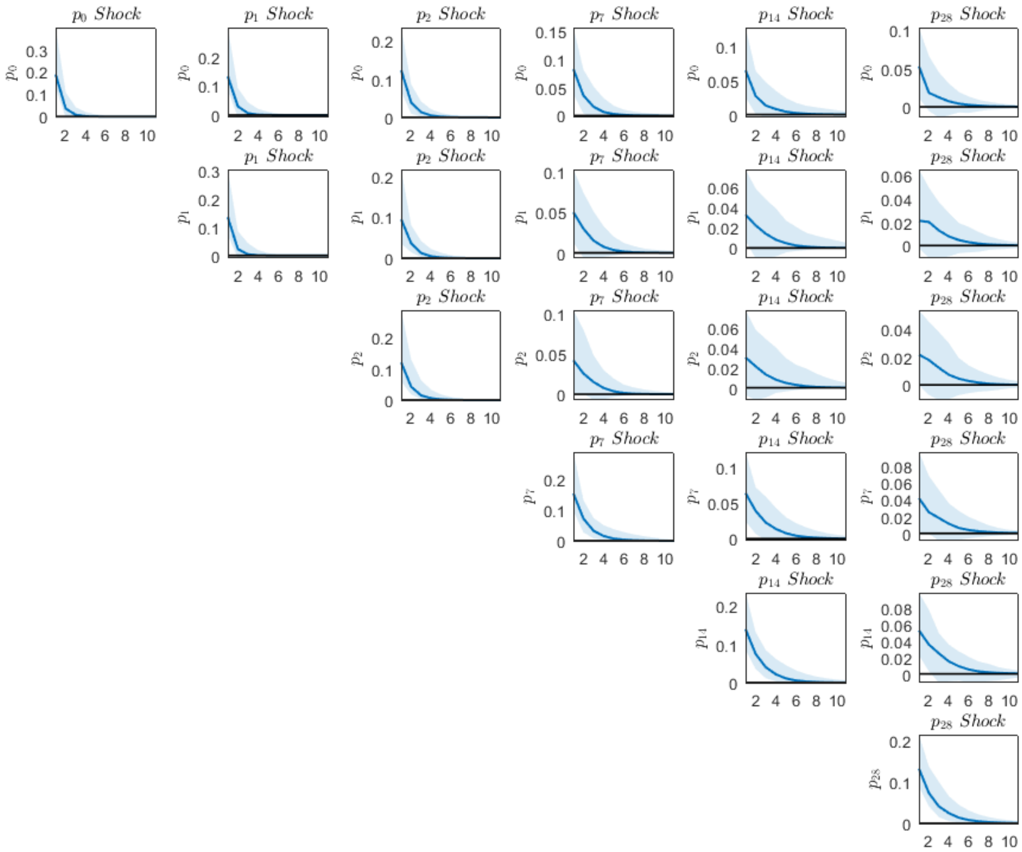
Figure 2: Distribution of the estimated autoregressive parameter $a_{i_{j^*,j}}$ parameters $j = j^* = \{0, 1, 2, 7, 14, 28\}$ and $i = \{0, 1, 2, \ldots, 107\}$



4.1 Advance booking effects

The SVAR approach also allows for an assessment of how shocks propagate both along the price trajectory and between subsequent arrival dates. We calculated the IRFs, as in (3), with horizon H. Figure 3 reports the average reaction (over the 107 hotels) to a one-standard deviation shock on price for an arrival date t (solid blue line) and the 90% confidence interval (shaded area).

Figure 3: Impulse response functions for system (1)-(2). Shaded blue areas denote 90% confidence bands.



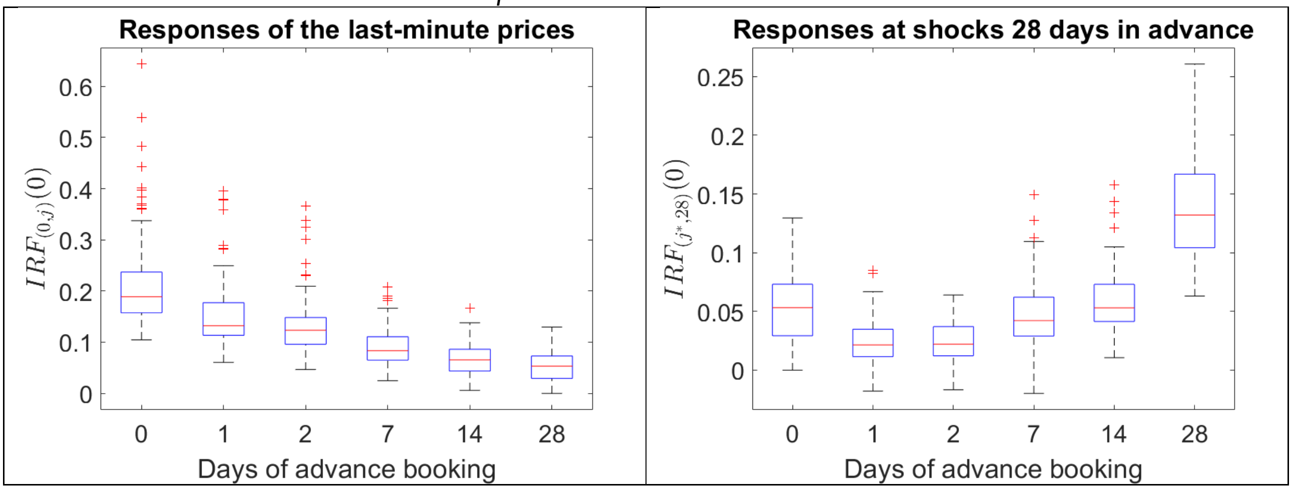
The first row of panels in Figure 3 displays the $IRF_{0,j}(h)$accounting for the response of $y_{t+h,t+h}$ (the price set in t+h for arrival date t+h i.e. with 0 advance booking) to $\varepsilon_{(t-j),t}$ (i.e. a one-standard deviation variation on price decided by the hotelier for arrival date *t* with $j = \{0, 1, 2, 7, 14, 28\}$ days advance). The second row reports $IRF_{1,j}(h)$ accounting for the response of $y_{t+h-1,t+h}$ to the same shock on price. Similarly, the last column reports $IRF_{j^*,28}(h)$, that is the response of the log price $y_{(t+h-j^*),t+h}$ (the price set for arrival date t+h at different advance booking $j^* = \{0, 1, 2, 7, 14, 28\}$) to $\varepsilon_{(t-28),t}$, (i.e. a one-standard deviation variation of the price for arrival date *t* decided by the hotelier with a $j = 28$ days advance).

The IRFs show that the responses are generally not significant for *h>3*, as the confidence interval includes the zero value. This suggests that the effects on the BAR of a new booking/cancellation for arrival date *t* do not last more than 2-3 days, reflecting the average length of stay in Milan and a weak management of customers' IRP across adjacent arrival dates. Indeed, customers expect price fluctuations for successive arrival dates due to seasonality or events, thus IRP management strategies are mainly targeted at keeping the price fair across the advance booking lags (given a fixed target date). Accordingly, we devoted special attention to the case $h = 0$, in order to investigate the effects of a shock on the prices on the arrival date.

The left panel in figure 4 summarizes the response of the last-minute prices to $\varepsilon_{t-j,t}$, namely $IRF_{0,j}(0)$. Such response reflects the tactical approach by hoteliers, or how they adjust the BAR for the target date according to the advance bookings. These responses are always greater than 0, therefore positive/negative shocks always have an effect on BARs with an equal sign. As expected, the mean price adjustment decreases monotonically; in particular, the effect of shocks decays as a negative exponential function of the advance booking, with significant reductions at advance bookings higher than 1. This reflects the greater impact of last-minute bookings or cancellations on pricing since, as the timeframe to confirm/cancel reduces, the hotelier becomes more confident about the effective demand for that date or about the difficulty to compensate current cancellations with future bookings.

The right panel summarizes the propagation of a one-standard deviation shock at $j = 28$, along the price trajectory, namely $IRF_{j^*,28}(0)$. It highlights the response of the log price $y_{(t-j^*),t}$ to $\varepsilon_{(t-28),t}$, i.e. the hoteliers' ability to manage the pricing for a target arrival date *t*, with four weeks advance. The average response describes a convex trajectory, with a maximum at $j^* = 28$, that is at the very moment in which the hotelier records the increase in occupancy rate for the arrival date *t*, and a minimum at 1-2 days before the arrival date. Accordingly, hotel managers are able to effectively manage prices in advance (i.e. to forecast the occupancy rate at different advance bookings). In fact, the selling price at 1-2 days before the arrival date is very similar to what it would have been if no shock had occurred at $j = 28$. On the other hand, the effect for $j^* = 0$ displays a significant increase reflecting a tactical attitude, in response to demand shocks. The BAR can be significantly decreased/increased in case of last-minute unexpected cancellations/bookings.

Figure 4: Left panel: impact of a one-standard deviation shock at each advance booking on price at target date. Right panel: impact of a one-standard deviation shock at advance booking 28 on the price trajectory for the same arrival date.



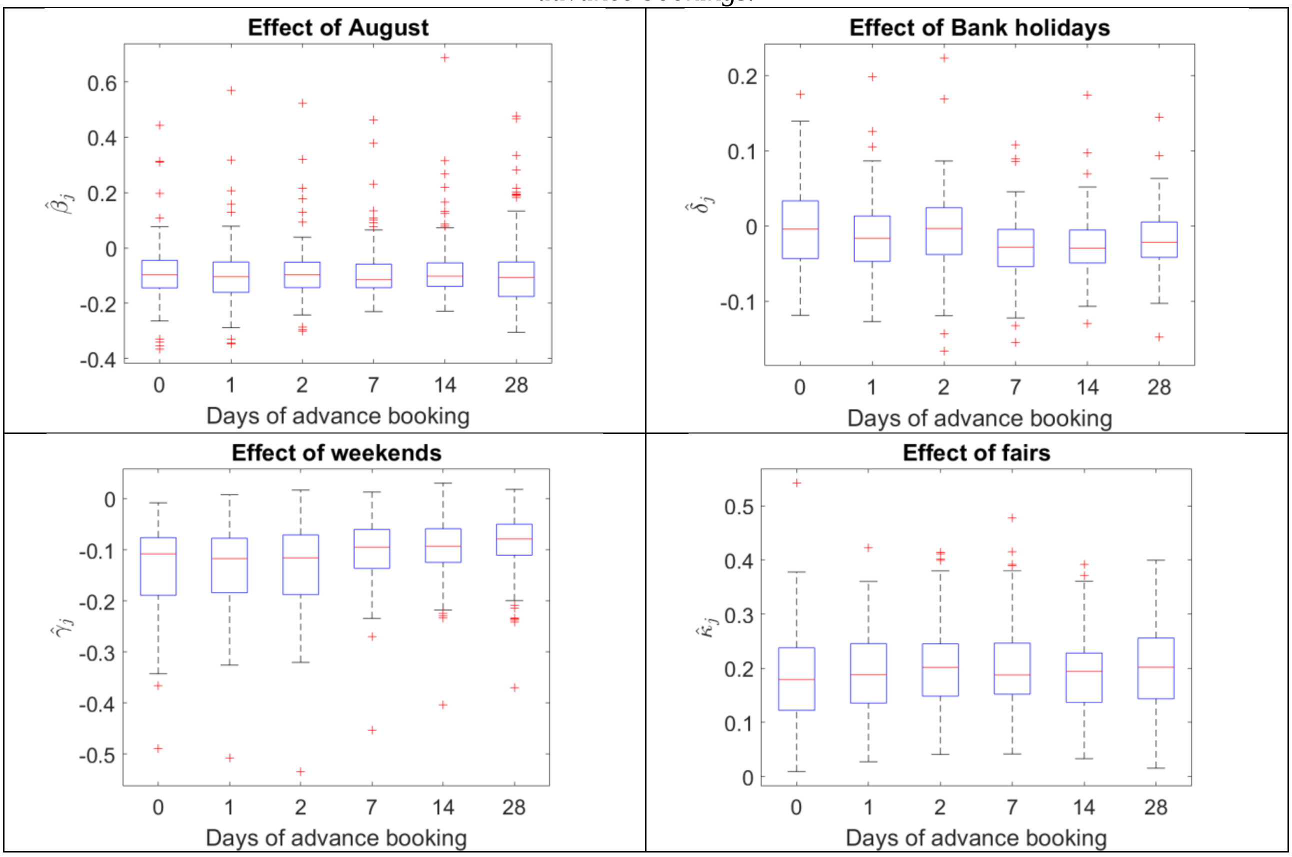
4.2 Seasonal, calendar, and fair exogenous effect

In Figure 5 we show the distribution of the estimated coefficients $\widehat{\beta_j}, \widehat{\gamma_j}, \widehat{\delta_j}, \widehat{\kappa_j}$ per advance booking. Intervals between extreme whiskers are set to 95%. The month of August has a negative effect, with no relevant differences among the advance bookings, indicating that the non-business season affects price levels, but not in a dynamic way. On the contrary, the effect of working days and weekends presents a more defined trend, as the negative "Friday to Sunday" effect becomes stronger approaching the last minute. This noteworthy increase in variability, suggests that hoteliers try to increase the occupancy rate at the last minute by leveraging the leisure segment, the most sensitive to online BAR discounts.

Bank holidays show a weaker negative impact on prices. Weakly negative values are observed for prices set with 1-2 weeks of advance booking, while they are almost null at 0-2 days of advance booking.
Fairs have the largest and positive effects on price levels, but no substantial differences across advance bookings. The calendar of fairs is, in fact, available well in advance, determining higher prices long before our 28 days observation horizon (strategy). The price drops between advance booking 2 and 0, when managers become less uncertain about the occupancy rate at the arrival date and tactics prevail over strategy. However, the magnitude of this drawdown is limited (less than 3 cents - in logarithm - corresponding to almost 5 euros), possibly due to an IRP effect across different sales channels. Often rooms are sold offline with discounted prices to different corporate customers, preventing the online prices from falling below the negotiated prices.

Overall, our first-stage results show that hoteliers use past occupancy rates, fairs and events, Bank holidays and seasonality, to set up pricing strategies and tactics across advance bookings.

F
igure 5: Distribution - over i= $\{0, 1, 2, \ldots, 107\}$ *hotels - of the effect of exogenous variables at different advance bookings.*

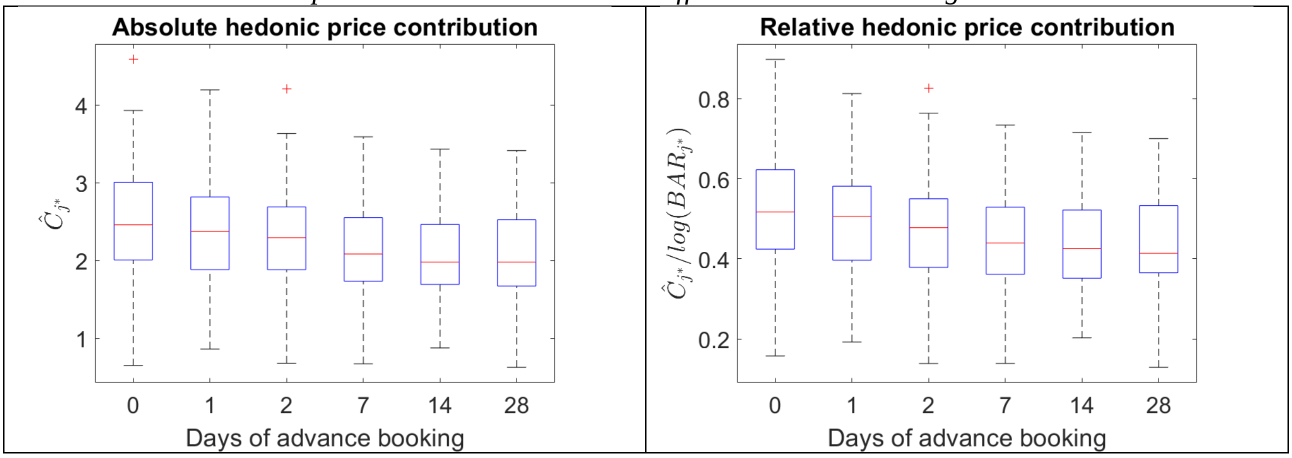


4.3 Hedonic pricing

In the second stage of our procedure, we focus on the constant term of the SVAR model $\hat{C}_{j^*}$ estimated in the first stage. This fixed effect summarizes (for each hotel i and advance booking j^*) the price

level due to the time-invariant characteristics of the service, once we have controlled for time-based pricing in model (1)-(2).
As expected, $\hat{C}_{j^*}$ is always positive (see Figure 6, lhs) with an average ranging from 2 to 2.5 depending on the considered j^*. However, we do not report significant differential effects across the advance bookings, even if both average values and variabilities increase as the advance booking decreases.
Given the log-linear form of the SVAR model, the ratio $\hat{C}_{j^*}/log(BAR_{j^*})$, reported in the right panel of Figure 6, represents the estimated weight of the service's time-invariant characteristics on the room rate at each advance booking. We call it the hedonic price contribution to BAR, i.e. the contribution by the internal characteristics of the service, while its complement to 1 is the dynamic price contribution to BAR.

Figure 6: Distribution - over i= $\{0, 1, 2, \dots, 107\}$ *hotels - of the absolute (lhs) and relative (rhs) hedonic price contribution to BAR at different advance bookings.*



Looking at the "average hotel", we find that its time-invariant characteristics contribute less than 50% to the BAR at higher advance bookings. For $j^* = 0$ the contribution reaches 52%, but interestingly we find values ranging from 16% to 91% for individual hotels. Although further hedonic analysis will be able to shed light on the reasons why we observe such high variability among hotels, we believe that a very important driver, not considered here, is the hotel's position on the Expedia.com pages. Appearing as a first result in a query allows for better and earlier exploitation of a service's feature even if it is not differentiated from competitors (with a positive effect on the marketing of a hotel's features).

Table 2 displays the outcomes of the OLS regression in equation (4). We do not report coefficients for variables: $dista$, nrs and $3stars$ since they were deleted in the specification phase as they were not significant at any advance booking. However – given the relevance of the number of stars in previous studies – it is worth noting that the estimated coefficients for the *3stars* variable were negative at any advance booking. Accordingly, star rating is positively correlated with customers' willingness to pay, even though the correlation is not significant in our sample. This could be due to the fact that the 15 3-star hotels we considered have an equivalent property value and/or they are not horizontally differentiated with respect to the other 4-star hotels in the sample. This hypothesis is supported by the fact that we choose accommodation structures close to the business district.

Table 2: Estimates, Hedonic model.

Estimates						
	$j^* = 0$	$j^* = 1$	$j^* = 2$	$j^* = 7$	$j^* = 14$	$j^* = 28$
$constant$	2.443(0.137) **	2.547(0.084) **	2.498(0.078) **	2.112(0.103) **	2.000(0.102) **	2.390(0.099) **
nmr	-0.057(0.019) **	-0.035(0.014) **	-0.040(0.013) **	-0.051(0.014) **	-0.050(0.014) **	-0.025(0.013) **
$nochain$	-	-	-	-	-	-0.221(0.120) **
$3stars$	0.003(0.001) *	-	-	0.003(0.001) **	0.003(0.001) **	-
$dist$	-0.032(0.013) **	-0.029(0.013) **	-0.030(0.012) **	-0.032(0.010) **	-0.027(0.009) **	-0.022(0.011) **
Goodness of fit						
F-test	6.096[0.001]	7.387[0.001]	10.630[0.000]	9.442[0.000]	8.504[0.000]	4.589[0.005]
$adj\ R^2$	0.136	0.116	0.166	0.207	0.188	0.120

Notes: Standard errors in parenthesis and p-values in brachets. Asterisks ** and * denote statistical significance at 5% and 10% rispectively. nmr is the number of meeting rooms, $nochain$ is a dummy variable with value 1 for no-chain hotels and $3stars$ is a dummy variable with value 1 for 3 stars hotels.

The analysis of the constant in the hedonic model confirms that the "baseline" value given to the room (net of the characteristics considered among the exogenous variables) tends to increase as the advance booking decreases. In other words, time-invariant services/attributes increase in hedonic value as advance booking decreases. The effect is partially driven by the shortage of hotel rooms that periodically affects last-minute bookings at this business-oriented destination. In high-peak weeks (when upper-scale hotels do not offer rooms) the business customers are willing to pay higher prices (considering it fair) even for hotels offering lower quality services.

Existing findings on hedonic pricing (see among others Lee and Jang (2011)) tell us that travellers are not only concerned about room availability, but also about location. In fact, we find that distance from the city centre has a significant and negative relationship with customers' willingness to pay. In particular, we show that this effect is lower at higher advance bookings, providing evidence that hotels located in the centre could gain larger advantages from customer segmentation for the last-minute bookings. Customers with the greatest spending capacity and the least flexibility on the dates of stay (the business travellers booking last-minute) are those with the greatest preference to stay close to the city centre. Thus, centrally located hotels can attach higher values to the services they offer, lowering the weight of the dynamic pricing component.

Meeting rooms show a significant negative impact on the average price without a clear dynamic across advance bookings. This evidence could be related to the fact that we are observing online prices of expensive hotels located in a central area. The internet is clearly the core distribution channel for leisure tourism, while hotels mostly focused on the business sector could be prone to competing on BARs since they are less attractive to holiday tourists (see Soler et al. (2019)).

Being an independent establishment and the hotel size (number of rooms) are two features that significantly differentiate their impact on a customer's willingness to pay at different advance bookings. The number of rooms has a significant positive effect only for some "mid-term" advance bookings. Being an independent hotel has a significant negative impact on price only for the early bookings ($j^* = 28$). The literature highlights that hotels belonging to a chain can request higher prices if the room sizes and property values are higher (Agmapisarn (2014)) or when customers perceive that the hotel offers a set of unique and valuable attributes (Silva et al. (2015)). Our findings could be explained by the fact that the hotels in our sample are not horizontally differentiated, yet chain affiliation is usually a signal of higher quality services (Israeli (2002)), especially for less-informed tourists. In fact, inbound leisure tourists are simultaneously the segment booking earlier and the segment seeking quality through an international brand, because they are less informed (more worried) about the quality standards of the Italian accommodation sector.

5 Conclusion

Online dynamic pricing has accustomed consumers to observe strong price fluctuations for the same product over the booking window where, we expect, the hedonic relationship could change rendering any characteristic/facility more or less important to the consumer's choice. To the best of our knowledge, in the existing literature there is no dynamic hedonic approach in this specific sense. Advance booking (booking time) is included as an explicative variable and the “time effect” is sometimes understood as price correlation among successive arrival dates or, more often, as the effect of special events and seasonality in modifying the consumers’ perceptions on the hedonic value of service attributes.

In this paper, we move ahead to the next step by suggesting an innovative method to estimate the implicit prices of service attributes along the advance booking, conditionally to the effects of dynamic pricing. In practice, we consider the price trajectory across the advance bookings as a multivariate endogenous variable in a SVAR framework. This permits us to model – in addition to the instantaneous price variation due to new booking/cancellations - the price interdependencies among different advance bookings, i.e. how hoteliers manage customer perceptions about relational prices. Additionally, the SVAR setting allows us to treat many of the tangible, reputation and contextual attributes of the service as fixed effects, whose value is estimated by the unit-specific means varying along the advance booking. The customers’ perceptions regarding the marginal contribution of these attributes is estimated in a second step by a conventional – static – hedonic model, considering the fixed effects of the SVAR model as dependent variables.

We find that advance booking matters in a business destination like Milan, as willingness to pay for a product/service attribute and its perceived value change during the booking window. Location is one of the most important variables affecting a customer’s willingness to pay; distance from the city centre has a lower effect at higher advance bookings. The number of rooms in a hotel has a significant positive effect only when customers book 1 or 2 weeks in advance. Being an independent hotel has a significant (and negative) price impact only in the early booking period, where inbound leisure tourists are more active on the internet compared to the higher spending segment (i.e. business tourists). Overall, we show that the other tangible, reputational and contextual attributes (not considered among the exogenous variables) tend to increase jointly in hedonic value as the booking window shrinks, reducing the weight of dynamic pricing practices.

Regarding time-based pricing, we show that hoteliers use fairs and events, Bank holidays and seasonality to manage along the advance booking the perceived value consumer give to tangible, reputation and contextual attributes. In particular, August, the non-business season, negatively affects the BARs but not in a dynamic way. On the contrary, Bank holidays and fairs are respectively associated to relatively large discounts and price increases in the early bookings while, at the last minute, hoteliers increase the magnitude of both discounts and overpricing to manage occupancy rates. In fact, if cancellations occur, a lower BAR is expected to be attractive for the leisure segment, which is the most sensitive to online BAR discounts, while a last-minute booking could be very expensive for walk-in guests when the occupancy rates exceeds hoteliers’ expectations.

Moreover, we prove that the online BARs are positively autocorrelated in the booking window. The correlation decreases significantly along the advance booking trajectory, reaching the minimum values for late booking ($j \leq 1$) where price trajectories show null and sometimes negative autocorrelations. We also show that the BAR adjustment caused by a shock (e.g. a change in occupancy rates for a fixed arrival date), decreases monotonically as a negative exponential function of the advance booking, with significant reductions at advance booking periods larger than one day. Both results clearly indicate the use of pricing tactics to avoid last minute decreases in occupancy rates when faced with unpredictable events such as cancellations. Symmetrically, strategy acquires importance at higher advance bookings lags, as hoteliers aim at keeping price trajectories stable or

not decreasing and variance low, in order to prevent speculative behaviour by customers (i.e. cancelling and rebooking) and to address the customers' internal reference price.
Finally, we prove that hoteliers can program prices in advance, meaning that they effectively forecast the occupancy rate at different advance booking. In fact, the average response to an early booking shock describes a convex trajectory, with a maximum at the very moment in which the hotelier records the increase in occupancy rate and a minimum at 1-2 days before the arrival date. For last minute booking $j^* = 0$ the effect shows a significant increase, corroborating our conclusion about a tactical attitude in response to unpredictable events like last minute cancellations and walk-in guests.

Several managerial implications arise. First, hotels offering meeting rooms should invest in direct or offline distribution channel (i.e. traditional travel management companies) in order to avoid price competition on the on-line market. Second, hotels located in the city centre can charge high rates close to the arrival date independently on the quality of offered services. Symmetrically, for hotels located far away from the centre, it may be more convenient to sell the most expensive rooms with large advance, to avoid the need for steep discounts on these high value assets in the last minutes. Third, a similar implication holds in general (i.e. for others attributes than meeting rooms and location) as their hedonic value increases as the advance booking period decreases. Thus, a hotel offering "premium" services should sell these in the early bookings, because in the last minute also the perceived value of standard attributes increases. An exception holds for horizontally differentiated hotels (able to segment customers) as the perceived value of the differentiated assets increases especially in the last-minute bookings. For example, a hotel with a differentiated SPA can valorise this attribute especially in the last minute, when its availability will increase significantly the perceived value of the stay for the demand segment interested in health care and wellness. Finally, IRP management strategies should be targeted at keeping a "fair" price dynamic along the advance booking trajectory changing the quality of the offered services in order to manage the most valuable attribute in accordance with the indications listed above. This will increase both the chance of early booking, and the hedonic value of the hotel tangible assets.

We are aware that this approach shows some limitations. From a methodological point of view, it could be possible to estimate simultaneously the two steps suggested in this paper adopting a structural panel-VAR setting. However, this would decrease the attractiveness to practitioners, since none of the existing statistical software allows for the estimation of the parameters and it would also be necessary to impose very complex additional restrictions.
Concerning the experimental design, we must recognize that our application explores only one city in detail, making use of the cheapest price offered for a one-person overnight stay, so that even robust results may be poorly generalizable. Moreover, due to the initial choice of relying only on OTA data and to the sampling technique, we do not analyse the effects on the online BAR of important time related variables, such as: reputation, occupancy rates, offline selling strategies, or position in which the hotel appears on the Expedia.com page. However, the proposed methodology is sufficiently flexible to consider these additional variables, so that future applications may provide a more general picture of the determinants of the hedonic value.

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