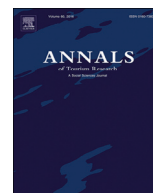




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## Hotel dynamic pricing, stochastic demand and covid-19

Andrea Guizzardi <sup>a,\*</sup>, Luca Vincenzo Ballestra <sup>a</sup>, Enzo D'Innocenzo <sup>b</sup>

<sup>a</sup> Department of Statistical Sciences, Alma Mater, Studiorum University of Bologna, Via delle Belle Arti 41, 40126 Bologna, Italy

<sup>b</sup> Department of Econometrics and Data Science, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, Netherlands



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### ABSTRACT

We develop an innovative framework to study how hoteliers apply inventory control and price discrimination taking into account seasonality. We end up with a time-varying model that, using publicly available information, connects the early booking and last-minute pricing decisions. In doing so, we account for the expected demand size and price elasticity, the inventory put on sales, and the last-minute demand shocks. An analysis focused on 100 hotels in Milan (Italy) shows that during the Covid-19 last-minute discounts/surcharges remain stable over long periods while the role of advance booking as a lever for revenue management is reduced. Moreover, the pandemic has increased the last-minute adjustment at the short advance booking, especially for midweek days.

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### Introduction

The Covid-19 has represented a serious structural break for the tourism and hospitality industry (Sharma & Nicolau, 2020), inducing unpredictable seasonal patterns also driven by government decrees Arabadzhyan et al. (2021). The extent to which hotels applies revenue management practices Zhang et al. (2020) and relies on innovations Sharma et al. (2021), have been affected by the Covid-19 pandemic, calling for new approaches able to leverage real time public data.

In this work, we propose a new theoretical model that explains the differences in the rates observed in the booking window on the basis of both the hoteliers' expectations about the customers' price elasticity, and the departures of the realized demand from that expected at the beginning of the booking window. That way, we shed light on whether and how the pandemic has changed the pricing and inventory control practices of accommodation structures, focusing on both the advance booking (dynamic pricing strategies for the same day of stay) and the seasonality (dynamic pricing strategies for different days of stay).

We accomplish this task by proposing a statistical approach to model (and potentially forecast) the price that a hotel posts on the Internet for a given day of stay based on the price that the same hotel posted for the same day of stay during the early booking period. To better cope with the dynamic features of the last-minute price adjustment, we employ a time series setting based on the score-driven approach proposed by Creal et al. (2011) and Harvey (2013). In doing so, we take into account the stochastic nature of seasonality allowing for asymmetric shocks and excess kurtosis in the distribution of the last-minute price. Such a methodology is new in the field of tourism and allows us to obtain valuable information about the market demand. Specifically, it provides qualitative and quantitative insight about the market segment mix expected by the hoteliers and the – stochastic – departures of the demand (due to unforeseen reservations/cancellations) from that expected at the beginning of the booking window.

\* Corresponding author.

E-mail addresses: [andrea.guizzardi@unibo.it](mailto:andrea.guizzardi@unibo.it) (A. Guizzardi), [luca.ballestra@unibo.it](mailto:luca.ballestra@unibo.it) (L.V. Ballestra), [e.dinnocenzo@vu.nl](mailto:e.dinnocenzo@vu.nl) (E. D'Innocenzo).

We test and compare our new dynamic approach against the standard static one. In the former, asymmetry and kurtosis of the price shock distribution – as well as its modal value and the variability – vary across calendar time. That way, we can model a large variety of seasonality patterns that may affect the hoteliers' pricing behaviors. Moreover, our approach does not require us to specify deterministic seasonal effects which are often difficult to model with a dichotomous (dummy) variable, especially when dealing with high frequency (daily) data. For instance, a dummy for weekends simply capture an average effect while the different weekends might not have the same impact on last-minute surcharges/discounts. Similarly, the effect of fairs and special events might not be the same across their duration, and/or they might generate spillovers that last “some days” before and/or after the events themselves. In addition, the use of dummy variables would require longer periods of observation and/or the exact knowledge of the events happening in the hotel's area, which researchers might not have when they analyze daily data to detect seasonality patterns (Yang et al., 2022).

We believe our approach is an important methodological advance in the field of tourism because it puts the spotlight on different aspects of the persistence of pricing behavior across seasons. For instance, by employing a dynamic specification for the kurtosis parameter, we can model the time dependence in the probability of observing extreme price shocks, assessing how such a probability varies between consecutive periods (e.g., across weekends and week-days). This would also allow one to establish if and how hotels apply dynamic pricing coherently with the general seasonality at the destination, even though this kind of analysis is beyond the scope of the present paper and might be left for a future work. Last, but not least, we underline that the proposed approach is based on publicly available data. Thus, it could be potentially applied to any destination or micro-area covered by an online travel agency. Understanding how hoteliers decide pricing strategies is undoubtedly a key point not only for revenue managers but also for a wider set of subjects involved in the travel and accommodation sectors (e.g., customers, travel agencies, policy-makers, etc.).

The empirical relationships that we estimate among early booking and last-minute rates are analyzed through the lens of an economic model of supply and stochastic demand. That way, we can shed light on the revenue managers' expectations about customers' price elasticities, market size and inventory management practices using a dynamic quantitative approach based on public data that outperforms usual static regression models.

The remainder of the paper is organized as follows: In [Section 2](#) we provide a review of the existing literature; in [Section 3](#) we develop the theoretical framework for intertemporal price discrimination, introducing the statistical models; in [Section 4](#) we perform the empirical analysis and we discuss the results obtained. Finally, in [Section 5](#) we provide some theoretical and empirical conclusions.

## Literature review

Demand seasonality, i.e., the time persistence in customers' behavior, is a relevant exogenous driver of dynamic pricing, see [Abrate et al. \(2012\)](#). A consolidated approach to account for seasonality consists of modeling the demand (e.g., arrivals) as a stochastic process specified by some econometric models ([Song et al., 2008](#)). Seasonality also plays a crucial role in the intertwined dynamics of quantities and prices, but, in the literature, the papers analyzing the relationship between tourism seasonality in quantities and prices are very few ([Lozano et al., 2021](#)). From the theoretical standpoint, [Croes and Semrad \(2012\)](#) support the idea that room rates follow stochastic dynamics that reflects hotel expectations about the demand on different arrival days. Accordingly, [Soler et al. \(2019\)](#) propose a hedonic model in which the price of the previous day is found to be the most relevant explanatory variable.

If seasonality determines a pattern of prices across the calendar time, we expect causal relations among rates to be identified also during the advance booking. Hotels use the price per night ([Jang et al., 2019](#)) and communication of room scarcity ([Teubner & Graul, 2020](#)) as two powerful marketing tools to differentiate their product across the booking window. Consumers, especially the ones paying more attention to hotel location or services, are becoming more and more sensitive to the price at early advance booking, as the perceived risk of not finding the desired hotel room/location increases at the last minute ([Guizzardi et al., 2017](#)). Then, we also expect a stochastic dependence between early booking and last-minute prices, which could be captured by (high-frequency) stochastic models. Indeed, managers can cheaply find all their competitors' prices on the Internet, and so the ability to read (high-frequency) time series of advance booking data has become more important than ever ([Tse & Poon, 2015](#)).

Past booking curves are the core information in pricing models ([Ivanov & Zhechev, 2012](#); [Webb, 2016](#)) and dynamic pricing algorithms employ the (usually negative) correlation between price and quantity to decide both pricing and inventory control strategies ([Mauri, 2013](#); [Tse & Poon, 2015](#)). However, when analyzing hotel pricing techniques based on public data, the utilization capacity is often not available, and thus the papers that model the interactions between prices and demand proxy the latter with the number of hotels with available rooms or the number of available rooms (see [Abrate et al. \(2012\)](#)). To overcome this issue, one can employ an economic (theoretical) approach based on the intersection between demand and supply ([Wan et al., 2020](#)). From the empirical standpoint, the effects of seasonality and advance booking on pricing are often studied using deterministic exogenous variables, e.g., the length of the advance booking (see, among others, [Abrate and Viglia \(2016\)](#)). However, by doing this, changes in the price levels are constrained to follow a pre-determined dynamics (often linear, see [Bigne et al. \(2021\)](#)). In other words, the pick-up rate is assumed to vary smoothly, but this is an unrealistic assumption because stochastic peak loads are possible ([Bilotkach et al., 2015](#)) and are very likely to characterize yield management interventions. It does not seem to be a coincidence that modern approaches to dynamic pricing have become increasingly sophisticated, with demand forecasting at the core of the algorithms ([Lee, 2018](#)). Simple time series models (e.g., the exponential smoothing) are giving way to

techniques based on empirical booking curves (Zakhary et al., 2008), and, more recently, to stochastic demand functions employing either a Poisson or a Bernoulli random component (Lee, 2018). The stochastic demand functions are considered the closest to the discreteness of consumer choices (Talluri & van Ryzin, 2005, p. 329) and are also used to jointly optimize assortment and prices (Li & Talluri, 2020).

New technologies have complicated the picture even more, transforming the pricing mechanism from an inventory control process to a customer-oriented approach (Vives et al., 2018). To this aim, (Schwartz, 2006) propose an extended advanced-booking generic-strategy decisional model to include consumer utility. Moreover, an ample literature on price fairness highlights the importance of the past pricing choices on consumer decision making (Choi & Mattila, 2018). The customers' perception of price fairness too is expected to show a kind of persistence, as is also confirmed by the fact that it impacts future bookings and, in turn, the capability of yield management systems to enhance profits (Ortega, 2016).

Further evidence that prices during the booking window move like an autoregressive stochastic process also comes from the analysis of (publicly available) online pricing data. Mohammed et al. (2021) highlight that rates' changes in the last-minute booking window depend on the price at the beginning of the week (a proxy of the current inventory). Abrate et al. (2019) suggest focusing on the variability and median of the prices during the advance booking to explain how hotels maximize revenues. In addition, a strong dependence structure among different advance bookings can also be observed when hotels try to prevent speculative behaviors of canceling and re-booking (Gorin et al., 2012). Finally, as shown by Mohammed et al. (2021), there is also reason to expect some degree of asymmetry between upward and downward movements (due to unforeseen reservations/cancellations).

Turning to the Covid-19, there is a general consensus on the fact that pricing strategies and (new) booking strategies can be an effective way to cope with the issues that the Covid-19 pandemic has caused in the accommodation industry Sigala (2020), even though the demand reduction and the unpredictable epidemic scenario have forced hoteliers to lower prices and reduce the range of their revenues management strategies Viglia et al. (2021). Several studies seem to indicate that the pandemic has changed the effect of seasonality and advance booking on pricing strategies. Giroux et al. (2022) assume that the Covid-19 crisis would lead travelers to prefer option sets with no price dispersion, while Zhang et al. (2020) show that tourists are expected to perceive price unfairness and disadvantaged price inequalities under the threat of Covid-19. Zhang et al. (2021) and Dolnicar and Zare (2020) report similar results, highlighting that in the peer-to-peer accommodation industry profit-driven hosts have disappeared and will leave the market to non-speculators, shifting the market back towards its original ethos. However, others mixed results have been published. For example, Piga et al. (2021) find that the role of structural and managerial factors in coping with the pandemic is not uniform between two apparently similar European metropolises such as London and Munich. Price differentials – relative to the pre-pandemic – are tied to hotel structural conditions only in London, where the highest segment hotels retain a significantly higher price premium than the lowest segment hotels. Moreover, in London price reductions are significantly more consistent for the hotels that already showed a higher price variability in the pre-pandemic period. Furthermore, in Munich the price surcharge for free cancellation is lower than the differential due to other price tactics. There is no evidence of this effect in London, where price reductions are distributed more uniformly across non-physical rate fences and hoteliers change their room portfolio more pro-actively (including breakfast and allowing more than 2 persons). Finally, Garrido-Moreno et al. (2021) provide evidence that cancellation management and flexibility measures are important factors determining the pricing behavior of Spanish hoteliers, even though they are the least relevant strategic measures to explain the variability of the empirical data.

## A statistical framework for intertemporal price discrimination

In this paper, we present a statistical model based on demand-supply intersection to describe the hoteliers' pricing decisions on a rational basis. This approach is consistent with previous papers in the accommodation literature, see, e.g., Croes and Semrad (2012), Wan et al. (2020) and Phillips (2021).

The role of the demand shocks, i.e., the departures from the pick-up rates planned/forecasted along the booking window, is well documented in the revenue management literature (see, e.g., Weatherford and Kimes (2003)). The booking curve is regarded as one of the main variables to pay attention to when setting the "right prices" in a fast-paced and dynamic booking environment (Webb, 2016). Accordingly, we assume that in the time interval between the arrival day  $t$  and the day  $t - k$ , managers use price as the pivotal variable to sell the planned quantity of rooms given their expectations on the price elasticity of the demand on different arrival days  $t$  (seasonality). They perform intertemporal price discrimination taking into account the customers' price elasticity (valuation) and the booking time (Su, 2007), with business travelers who tend to be more price inelastic and plan their journey less in advance than leisure travelers (Alderighi et al., 2015).

Managers set an inventory management strategy before opening the reservations for day  $t$ , limiting the number of available rooms offered to ensure that there will be availability until the end of the booking window (Weatherford & Bodily, 1992). Then, they track the booking curve and observe - in real-time - the differences between the planned inventory and the number of rooms sold. Unexpected reservations/cancellations modify the number of rooms offered by hotels (inventory control), who consequently update the price (dynamic pricing) of the rooms on sale at the highest advance bookings. This process is also known as stochastic peak load pricing, see Lott and Roberts (1991) and Bilotkach et al. (2015). Finally, we also assume that, for better market segmentation, hotels use different distribution channels, but any information available on any channel is used to (re)determine the number and the price of the rooms allocated to each channel.

The theoretical model

More formally, let  $t$  denote the arrival date in a given hotel. We assume that the booking window is divided into  $k$  time intervals where offered quantities and prices are kept constant. For the sake of simplicity, we consider time intervals of length 1 day (quantities and prices are updated every day), but other lengths could be considered as well, provided that the number of updates does not depend on the day of stay  $t$ . The number of rooms a hotel offers online in  $t - k$  for a stay in  $t$  is  $Q_{t,k} + S_{t,k+1}$ , where  $Q_{t,k}$  is the number of rooms the hotel planned to sell according to the initial inventory management strategy and  $S_{t,k+1}$  is a random variable that accounts for the effect of the demand shock (unexpected reservations/cancellations) observed in  $t - (k + 1)$  on all the distribution channels. Note that, unlike Phillips (2021), who assumes that revenue managers decide supply by optimizing profit based on the probability distribution of the demand they perceive at the beginning of the booking window, we postulate that hoteliers regularly update the number of rooms put on sale based on the demand observed. That is, in  $t - k$  the hotel looks at the excess/shortage of rooms sold on all the distribution channels up to day  $t - (k + 1)$ , and modifies the number of rooms to sell accordingly. Moreover, let  $P_{t,k}$  denote the price posted in  $t - k$  for a stay in  $t$ . The expected demand is given by:

$$Q_{t,k}^* = a_{t,k} - d_{t,k}P_{t,k}, \tag{1}$$

where  $a_{t,k}$  is the maximum hypothetical demand in the case of price equal to 0 in  $t - k$ , which only depends on the structural features of the hotel (e.g., the travelers who are interested in the hotel due to its location or service), and  $d_{t,k}$  is the average sensitivity of the demand to the price. The hotel calibrates all the parameters looking at the information set at the beginning of the booking window.

These parameters can vary with seasonality  $t$  and advance booking  $k$ , but we assume that the ratios  $\frac{a_{t,k-1}}{a_{t,k}}$  and  $\frac{d_{t,k-1}}{d_{t,k}}$  do not depend on  $t$ . Accordingly, the term  $\frac{a_{t,0}}{a_{t,k}} \frac{d_{t,k}}{d_{t,0}}$  does depend on  $t$ .

Therefore, on the first day of the booking window, i.e., on  $(t - k)$ , the hotel sets the expected demand equal to the number of rooms offered, that is  $Q_{t,k}^* = Q_{t,k} + S_{t,k+1}$ . Using this equation and Eq. (1), we obtain the hotel asking price:

$$P_{t,k} = \frac{a_{t,k} - Q_{t,k} - S_{t,k+1}}{d_{t,k}}. \tag{2}$$

On the second day ( $t - k + 1$ ), the number of rooms offered is  $Q_{t,k-1} + S_{t,k}$  ( $S_{t,k}$  being the adjustment on the number of rooms put on sale in  $t - (k + 1)$  due to the number of rooms sold up to day  $t - k$ ), and the expected demand is  $Q_{t,k-1}^* = a_{t,k-1} - d_{t,k-1}P_{t,k-1}$ . Therefore, the new price will be:

$$P_{t,k-1} = \frac{a_{t,k-1} - Q_{t,k-1} - S_{t,k}}{d_{t,k-1}}. \tag{3}$$

Then, if we obtain  $a_{t,k}$  from Eq. (2), we have

$$a_{t,k} = Q_{t,k} + S_{t,k+1} + d_{t,k}P_{t,k}. \tag{4}$$

Substitution of Eq. (4) in Eq. (3) yields

$$P_{t,k-1} = \frac{\frac{a_{t,k-1}}{a_{t,k}} (Q_{t,k} + S_{t,k+1}) - Q_{t,k-1} - S_{t,k}}{d_{t,k-1}} + \frac{a_{t,k-1}}{d_{t,k-1}} \frac{d_{t,k}}{a_{t,k}} P_{t,k}. \tag{5}$$

Relation Eq. (5) can be extended for  $k - 2, k - 3, \dots, 0$ . In particular, by imposing  $Q_{t,0}^* = Q_{t,0} + S_{t,1}$ , we have  $P_{t,0} = \frac{a_{t,0} - Q_{t,0} - S_{t,1}}{d_{t,0}}$ , and by using Eq. (2) we obtain

$$P_{t,0} = \frac{\frac{a_{t,0}}{a_{t,k}} (Q_{t,k} + S_{t,k+1}) - Q_{t,0} - S_{t,k}}{d_{t,0}} + \frac{a_{t,0}}{d_{t,0}} \frac{d_{t,k}}{a_{t,k}} P_{t,k}. \tag{6}$$

Relation Eq. (6) expresses the last-minute price  $P_{t,0}$  as a linear function of the price  $P_{t,k}$  asked at the beginning of the booking window of length  $k$ . By defining

$$\mu_{t,k}^* = \frac{\frac{a_{t,0}}{a_{t,k}} (Q_{t,k} + S_{t,k+1}) - Q_{t,0}}{d_{t,0}}, \quad 1cmb_k = \frac{a_{t,0}}{a_{t,k}} \frac{d_{t,k}}{d_{t,0}}, \quad \eta_{t,0} = \frac{-S_{t,1}}{d_{t,0}}, \tag{7}$$

we can rewrite Eq. (6) in a more compact form:

$$P_{t,0} = \mu_{t,k}^* + b_k P_{t,k} + \eta_{t,0}. \tag{8}$$

Note that the term  $\mu_{t,k}^*$  is known at the beginning of the booking window, whereas  $\eta_{t,0}$  is not. In line with our previous assumptions,  $\mu_{t,k}^*$  can depend on the seasonality and the advance booking, whereas  $b_k$  only depends on  $k$ .

Eq. (8) accounts for the time-based theory according to which hotels may apply inter-temporal price discrimination and inventory control for advance booking  $k$ . In particular,  $P_{t,0}$  is specified as the sum of three terms that are well established in the revenue management literature. The parameter  $\mu_{t,k}^*$  is the contribution to the price in  $t$  that is fixed by the manager in  $t - k$  and is not proportional to the price  $P_{t,k}$ . We note that it depends on the rooms that the hotel planned to sell in  $t$  and  $t - k$  set by the inventory management strategy, and on the demand shock observed in  $t - (k + 1)$ , namely  $\varsigma_{t, k+1}$ . Thus,  $\mu_{t,k}^*$  represents an inventory-based advance booking discount/surcharge.

The term  $b_k P_{t,k}$  accounts for both inter-temporal price discrimination and product differentiation effects, as prices can also vary with the room quality. As clearly indicated in our model, the parameter  $b_k$  reflects the “relative strength” of the expected market conditions in  $t$  (namely, the size of potential demand and/or the price elasticity) with respect to those observed in  $t - k$  (Guizzardi et al. (2017), Mohammed et al. (2021)). Its value is greater than 1 when, in  $t - k$ , the manager is confident that the ratio  $\frac{a_{t,0}}{a_{t,k}}$ , measuring the change in potential hotel demand due to structural characteristics, will be greater than the ratio between the expected price sensitivities  $\frac{d_{t,0}}{d_{t,k}}$ . In other words, we have  $b_k < 1$  if  $\frac{a_{t,0}}{d_{t,0}} < \frac{a_{t,k}}{d_{t,k}}$  that is, if the hotel expects the market to be less favourable in  $t$  than in  $t - k$ . This case is likely to occur when hotels have structural features that are highly requested by the demand segment booking in  $t - k$  and/or less requested by those booking in  $t$ , while the price elasticity is not very different between the two periods. In such a scenario, the hotel will try to sell the majority of rooms at time  $t - k$  and only few rooms at the last minute, even accepting discounts. The value  $b_k$  could also be affected by (unobservable) second-order price discrimination practices. If the “old good RM rule” to sell the best rooms first is followed (Escoffier, 1997), we expect to find a small  $b_k$  coefficient.

The third contribution, equal to  $\eta_{t,0}$ , is due to the shocks on the demand in  $t - 1$  (a measure of the error in forecasting the pick-up curve in  $t - 1$ ).

For any fixed  $k$ , to better cope with the time dependence of the demand shocks, it is convenient to consider the following term:

$$\varepsilon_{t,k} = \mu_{t,k}^* + \eta_{t,0}, \tag{9}$$

so that

$$P_{t,0} = b_k P_{t,k} + \varepsilon_{t,k}. \tag{10}$$

According to Eq. (10), we can regard  $\varepsilon_{t,k}$  as a random component that measures the deviation of  $P_{t,0}$  from  $b_k P_{t,k}$ . That is,  $\varepsilon_{t,k}$  is the price-correction that the hotel will adopt on day  $t$  for a stay on the same day, given the planned inventory (the intertemporal pricing strategy used to segment the market) and the demand shock observed on day  $t - 1$  for the stay in  $t$ . It represents the error of the last-minute price forecasted by the manager in  $t - k$ . For the sake of simplicity, we will also call it price shock or last-minute price adjustment.

### The stochastic framework

The expectations on the demand that hoteliers have at the beginning of the booking window (expectations that are based, for instance, on the demand observed in previous years/periods) will not necessarily be met by the (future) realized demand. The gap between the realized and expected demand may generate a last-minute price adjustment, which we model using a time varying probability distribution. In other words, we consider the last-minute discounts/surcharges  $\varepsilon_{t,k}$  “stochastic” (throughout this paper, we use the adjective “stochastic” to compactly refer to the fact that shocks - or other quantities of interest - are random variables with a time-varying probability distribution).

We may assume different shapes for  $\varepsilon_{t,k}$ . The simplest one is a non-central normal with a constant mean and standard deviation. In light of the evidence in the literature (see for example Hung et al. (2010) and Guo et al. (2021)), a more realistic alternative would be to consider a skew- $t$  distribution, which allows us to take into account the possible asymmetry and the high kurtosis of the price shocks. Given a booking window  $[0, k]$ , the skewness determines whether the price shocks are more likely to be positive or negative, or, in other words, if they occur due to unexpected reservations rather than cancellations. The kurtosis measures the probability of observing “extreme” relative price shocks, providing information about dynamic pricing choices in “extreme” situations (e.g., when the unexpected demand leads to/away from the capacity saturation).

Both the above distributions assume that the shape of  $\varepsilon_{t,k}$  does not depend on seasonality (but only on the chosen advance booking  $k$ ). However, we know that, in large metropolitan areas characterized by both leisure and business tourism, seasonality is crucial in defining the expected demand and the consumers’ sensitivity to prices, inducing a correlation between prices for subsequent arrival days.



Therefore, we also explore a third possibility using a score-driven approach model (see, for example, Creal et al. (2011) and Harvey (2013)), where we assume the parameters of the distribution of  $\varepsilon_{t,k}$  (namely the location  $\mu_{t,k}$ , the scale  $\varphi_{t,k}$ , the degrees of freedom  $\nu_{t,k}$  and the asymmetry  $\gamma_{t,k}$ ), are time dependent. Allowing the price shock distribution parameters to vary with time, we expect to obtain a better fit, since we can consider short term (even daily) seasonal effects.

It is worth pointing out that weekends, fairs and special events could also be dealt with by introducing dummy variables. However, this procedure, albeit very common in the tourism literature, has some disadvantages. First, it assumes that all the week-ends, fairs and special events have the same effect on the demand, and do not overlap each other. Otherwise, even if we employ one dummy for each of the main fairs, week-ends or special events, the questionable implicit assumption is that the demand remains constant every day. Finally, the use of dummy variables requires exact knowledge of the events happening in the hotel's area, which researchers usually do not have, especially if they deal with daily observations or with not enough long periods (Yang et al., 2022).

According to the score-driven approach, each parameter of the  $\varepsilon_{t,k}$  distribution is specified through a recursive equation that involves two main contributions, one proportional to the score of the log-density and the other being an autoregressive term of the order 1. When the value of the coefficient of the autoregressive term is close to 1, the corresponding parameter of the price shock distribution tends to persist. Even though the analysis of the dynamics of location, scale, kurtosis and skewness of the price shock is beyond the scope of this work, we argue that it constitutes a criterion to read how dynamic pricing is applied across seasons.

### The econometric models

We outline the three econometric models that we are going to estimate and compare in the empirical application.:

$$\textbf{Model 1: } P_{t,0} = b_k P_{t,k} + \varepsilon_{t,k}, \quad \varepsilon_{t,k} \stackrel{iid}{\sim} \mathcal{N}(\mu_k, \varphi_k^2), \quad (11)$$

$$\textbf{Model 2: } P_{t,0} = b_k P_{t,k} + \varepsilon_{t,k}, \quad \varepsilon_{t,k} \stackrel{iid}{\sim} \text{Skew-}t(\mu_k, \varphi_k^2, \nu_k, \gamma_k). \quad (12)$$

$$\textbf{Model 3: } P_{t,0} = b_k P_{t,k} + \varepsilon_{t,k}, \quad \varepsilon_{t,k} | \mathcal{F}_{t-1}^k \sim \text{Skew-}t(\mu_{t,k}, \varphi_{t,k}^2, \nu_{t,k}, \gamma_{t,k}). \quad (13)$$

For more technical details about the specification and the estimation of the above models, the reader is referred to the online supplementary material. Here, we only observe that in the estimation procedure we also accounted for possible endogeneity issues, using the nonlinear instrumental variable method proposed by Hansen et al. (2010), see the online supplementary material.

### Data and results

We perform an empirical analysis focusing on the city of Milan, the first Italian NUTS3 area in the European GDP per capita ranking. Head-quartering the Italian stock market and hosting several multinational holdings in the mechanics and fashion sectors, Milan has the largest exhibition center in Europe with a total area of 753,000 square meters.

The tourism supply is mixed, with 474 hotels (142 of which are 4-star hotels, the most popular category in the city), and 17,659 registered shared economy properties in 2019, 60 % of which were single listing properties (Amore et al., 2020). In 2015, Milan hosted the Expo, which generated a strong positive impact on the city's performance and increased the number of leisure clients (Sainaghi et al., 2019).

However, the pre-Covid-19 tourism market (2019) was mainly business-oriented. The city hosted more than 8 million tourists in its hotel structures, while, due to the Covid-19 pandemic, in 2021 the overnight sales fall to 3.5 million, giving rise to a new seasonal pattern less conditioned by fairs and other business or fashion events.

On March 10, 2020, the Italian Ministry issued a decree limiting the movement of individuals throughout Italy, unless specifically authorized for work or healthcare. On June 3, freedom of movement across regions and towards other European countries was restored, albeit with security constraints and social distancing measures that prevented some accommodation structures from operating at full capacity. In October, the second wave of the pandemic forced the Italian Government to introduce further restrictions that were gradually removed starting from May 2021. Accordingly, we collect data (from booking.com) from January 30, 2019 to November 11, 2020 and we consider the Covid-19 sample from March 10, 2020 to November 11, 2020 (250 days) and a pre-Covid-19 sample from February 27, 2019 to March 9, 2020 (376 days).

The proposed model can be used to study the pricing behavior for any advance booking, though our analysis considers advance bookings of 7, 14 and 28 days. Horizons longer than 28 days are excluded to eliminate the issues of missing data at the beginning of the time period. For example, the price for a stay on February 27 - booked 28 days in advance - is available only if we scrape data on January 30. Moreover, we operationalize the concept of "last-minute price" by considering  $k = 1$  when the price for  $k = 0$  for any kind of room is missing.

With the aid of a web-scraping software we simulate a customer searching for a room at each of four different advance booking periods. We 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. The room most frequently offered at the last minute is a non-refundable, double room for single use with breakfast included. The importance of free cancellations increases with the size of the advance booking window, but we use non-refundable rates as our standard because we want to perform a comparative analysis where the seasonality and advance booking dimensions vary but the product put on sale remain the same. Instead, if we used refundable rates, we would not consider rooms with the same “intrinsic value” at different advance bookings. Indeed, for example, a refundable rate offered at  $k = 7$  implies a different cancellation risk than a refundable rate offered at  $k = 28$  or  $k = 0$ . To deal with the problem of missing non-refundable, double room for single use with breakfast included rates at some  $t$  and  $k$ , we adjust the published prices by means of auxiliary regressions. For instance, if the price of a single use double room is missing, but the price of a single room is available (same  $t$  and  $k$ ) we estimate the former as the output of a simple linear regression in which the price of the single room is the only independent variable. If at least one between the intercept and the slope parameters is not highly significant ( $p$ -value  $> 1\%$ ), the missing value is not inferred. A similar procedure is used to estimate missing non-refundable rates when refundable prices are published. By contrast, missing breakfast-included rates are obtained by adding the cost of breakfast or by subtracting the cost of lunch, as we note that these surcharge/discount rates are not subject to dynamic pricing (for a given hotel, they are the same for almost every  $t$  and  $k$ ). This is similar to the common approach of adding dummy variables in the estimated models (see among others [Yang and Leung \(2018\)](#)), but it allows us to keep the model more simple, and use all the prices an hotelier publishes (any  $t$  and  $k$ ) when the non-refundable, double room for single use with breakfast price is missing.

We focus on a panel of 100 hotels. Low and mid-segment hotels are excluded, as they have a lower propensity to dynamic pricing and electronic distribution practices ([Dabas & Manaktola, 2007](#)). The total closure of the MICE segment due to the Covid-19 had a great impact on the tourism demand, reducing both levels and (seasonal) peaks. The effect on prices is particularly evident if we look at the descriptive statistics reported in [Table 1](#). In the Covid-19 period, the 90th percentile of  $P_{t,k}$  fell on average by 17%. The minimum rates, affected by the higher marginal costs due to the Covid-19 safety protocols, show a more moderate reduction, and, for  $k = 0$ , the 10th percentile even increased by 2.5 Euros.

We observe that the mean prices during the Covid-19 period are inversely proportional to the advance booking, whereas in the pre-Covid-19 they show a minimum at  $k = 0$ . Consequently, the decline in the average price due to Covid-19 goes from 45 Euros for  $k = 28$  to only 13 Euros for last-minute bookings ( $k = 0$ ).

Covid-19 also lowered the price variability at all the considered advance bookings, with only one exception being the rates proposed to “walk-in” guests ( $k = 0$ ), which might be due to heterogeneity in performances across hotels and also to different tactical response of hotels to the pandemic.

This means that the Covid-19 pandemic has reduced the hotel's ability to enhance their distinctive features during advance booking periods. Hotels now differentiate their products leveraging the Covid-19 safety rules and do this mostly at the last minute, when information about cleaning or disinfecting procedures and social distancing measures are the most important reasons to choose an accommodation, according to a panel of corporate travel managers we interviewed.

We report in the online supplementary material the distribution of the last-minute prices for a selection of 6 hotels with different star-rating, capacity, and brand affiliation. In all cases, the plots show that rates are not distributed normally and have experienced a strong reduction due to Covid-19.

The box-plots in [Fig. 1](#) exhibit some interesting features that confirm price departure from normality at the different  $k$ .

For example, the kurtosis is higher than 3 for almost all hotels, revealing that extreme prices occur with high frequency. It increases monotonically with advance booking signaling that in the early stages hotels use small price variations while as the date of stay approaches, they offer larger discounts/surcharges ([Kim et al., 2009](#)). Similarly, the majority of the times the skewness is greater than zero, which indicates that surcharges are less frequent than discounts. Both the kurtosis and the asymmetry levels (and the dispersion) increase as  $k$  decreases, highlighting that in Milan there is strong competition for the last-minute customers through extreme pricing discounts.

**Table 1**  
Descriptive statistics of the hotel prices at different advance bookings.

	Mean	Median	Std. Dev.	$q_{10}$	$q_{90}$
Pre-Covid-19					
$k = 0$	184.97	142.46	157.67	71.00	326.50
$k = 7$	186.40	145.07	154.62	73.50	324.00
$k = 14$	189.42	156.00	137.28	77.00	321.79
$k = 28$	196.83	164.50	138.89	73.37	330.22
During-Covid-19					
$k = 0$	171.30	131.90	185.08	73.50	283.30
$k = 7$	160.47	131.66	119.37	73.50	269.92
$k = 14$	154.08	130.13	96.54	72.40	265.59
$k = 28$	155.92	132.50	96.13	73.50	272.35



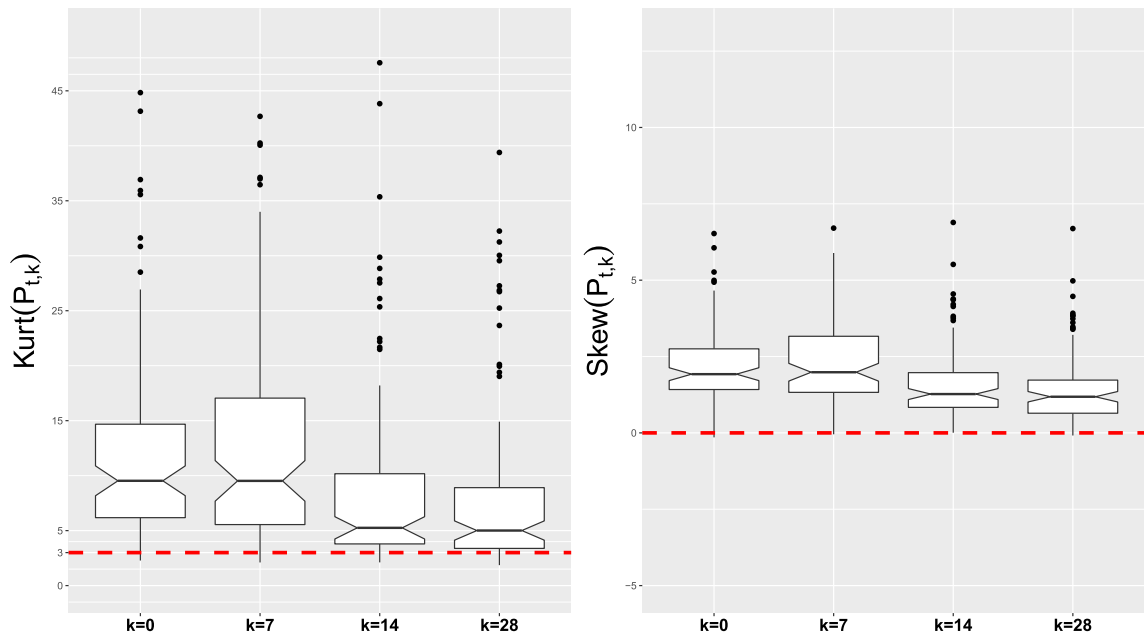


Fig. 1. Price kurtosis (left) and skewness (right) in the pre-Covid-19 period at different advanced bookings. The dashed red line indicates the theoretical standard Gaussian tails.

Seasonality  $t$  is very important, but Covid-19 has reduced its impact. In fact, fewer extreme prices are seen during the pandemic (e.g., the median and specifically the 90th percentile of the kurtosis are lower than pre-Covid-19). Moreover, the price distributions become more symmetric and there are more hotels with negatively skewed prices, especially for the longest advance bookings (see Fig. 2). This can be explained considering that, during the pandemic, some hotels followed temporary virtual channel closure strategy (Oses et al., 2016), publishing rates so high that virtually no customer would consider them fair.

The pandemic has also reduced the hotel heterogeneity for frequency of extreme last-minute surcharges or discounts, especially for the lowest  $k$ . The most evident differences are observed for  $k = 7$ , which, in the pre-Covid-19 sample, is the advance

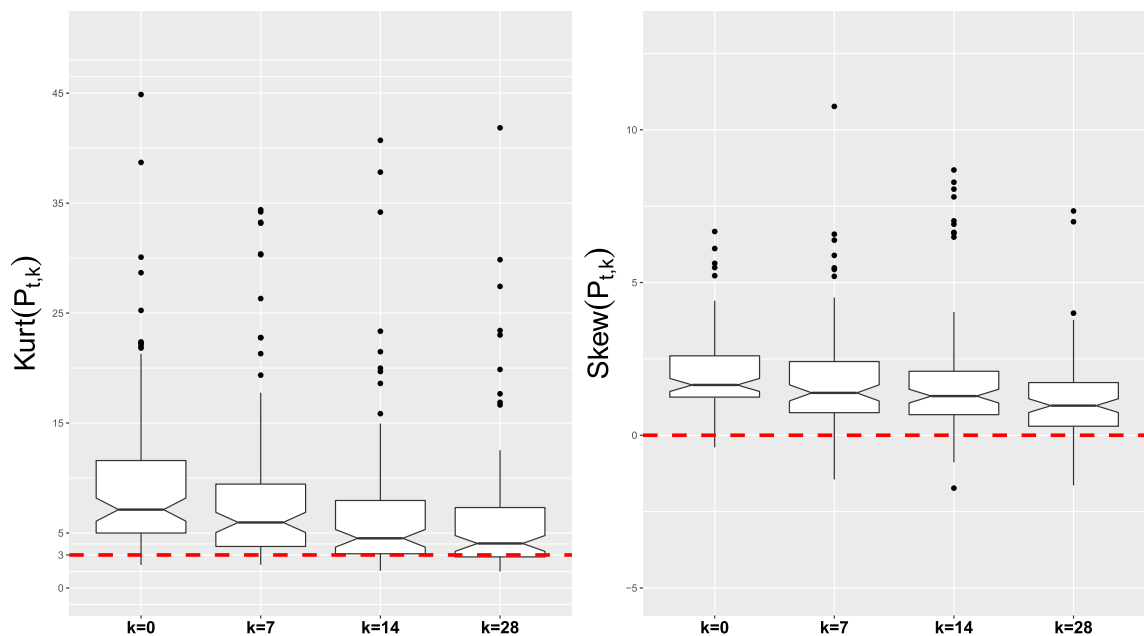


Fig. 2. Price kurtosis (left) and skewness (right) in the Covid-19 period at different advanced bookings. The dashed red line indicates the theoretical standard Gaussian tails.

booking with the most heterogeneous skewness and kurtosis driven by the simultaneous presence of significant business and leisure demand.

*Estimation results*

In the previous Section, we showed that the price shocks tend to depart from normality. So, it should not be surprising that the goodness-of-fit of *Model 1* is significantly different (and lower) than the goodness-of-fit obtained when the price shock  $\varepsilon_{t, k}$  is modeled as a skew- $t$ . In particular, we find that for both the pre-Covid-19 and the Covid-19 periods and for  $k = 7$  and  $k = 14$ , *Model 2* outperforms *Model 1* for all the hotels in terms of both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). A similar result holds for  $k = 28$ , with the only exception being one hotel where *Model 1* yields better AIC and BIC than *Model 2* for both the periods.

The flexibility of *Model 2* to capture tail thickness and skewness provides a considerable improvement in goodness-of-fit. Then, using a skew- $t$  distribution, we can obtain a more realistic representation of the last-minute price adjustment. However, since *Model 1* and *Model 2* are static models, they do not allow us to fully exploit the information contained in the last-minute price shock  $\varepsilon_{t, k}$ . Therefore, we cannot model the fact that hotels can manage capacity constraints by charging higher prices during periods of higher demand (peak-load pricing), or even that they can be systematically wrong in forecasting the last-minute demand in adjacent arrival days. Consistently, using a dynamic model provides a significant improvement. *Model 3* outperforms *Model 2* in the AIC and BIC criteria for more than 95% of the hotels and all the considered  $k$ . So, in the following we will only consider the models with static and dynamic skew- $t$  residuals.

Figs. 3 and 4 show the distribution of the estimated parameters  $\mu_k$  and  $b_k$ , respectively, for *Model 2* and Fig. 5 reports the distribution of the estimated  $b_k$  for *Model 3* (the values of  $\mu_{t, k}$  for *Model 3* are not reported as they are time series). For both the specifications, all parameters exhibit monotone dependence on  $k$ . The price shocks  $\mu_k$  tend to decrease as the last minute is approaching, while the estimates  $b_k$  tend to assume the highest values (and the highest dispersion) at the last-minute.

If we compare the results for the Covid-19 period with pre-Covid-19, we note an upward shift of the  $b_k$  values, while the parameters  $\mu_k$  decrease, especially at the highest lags. We argue that this fact reflects the Covid-19 travel restrictions wiping out the leisure segment, which is more elastic to price and tends to book earlier than the business segment. Consequently, both the ratio  $\frac{a_{t,0}}{a_{t,k}}$  and  $\frac{d_{t,k}}{d_{t,0}}$  have increased. The decrease in the median value of the  $\mu_k$  parameter is consistent with a shift in inventory allocation due to Covid-19, since, following relation (7), the number of rooms offered at the longest advance bookings ( $Q_k + \varsigma_{t, k+1}$ ) has declined allowing  $Q_0$  to increase.

The  $b_k$  coefficients of the dynamic model (see Fig. 5) show similar patterns, even if the estimated values are smaller than in *Model 2* and are almost always smaller than 1. This is not surprising, as the seasonal effect on dynamic pricing (which in *Model 2* was accounted for only through price  $P_{t, k}$ ) is now also captured by the time varying parameters  $\mu_{t, k}$ . In addition, the coefficients  $b_k$  show a lower dispersion than in *Model 2*. This is again reasonable since the assumption that the last-minute price adjustment is time dependent provides more flexibility in modeling the pricing strategies that hotels use to segment the

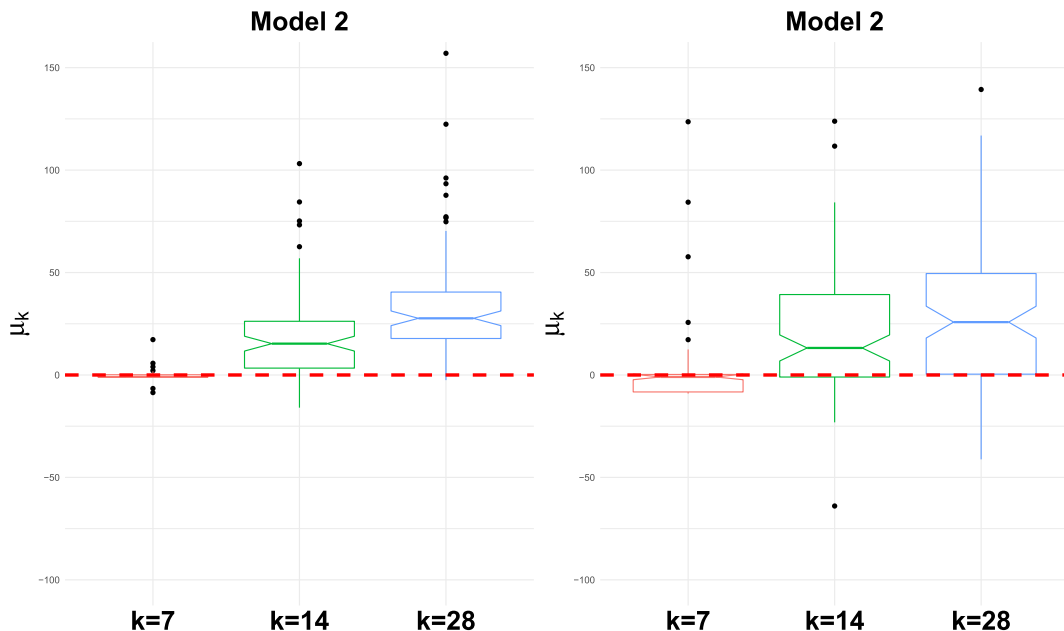


Fig. 3. Estimated  $\mu_k$  coefficients, in the pre-Covid-19 (left) and the Covid-19 periods.

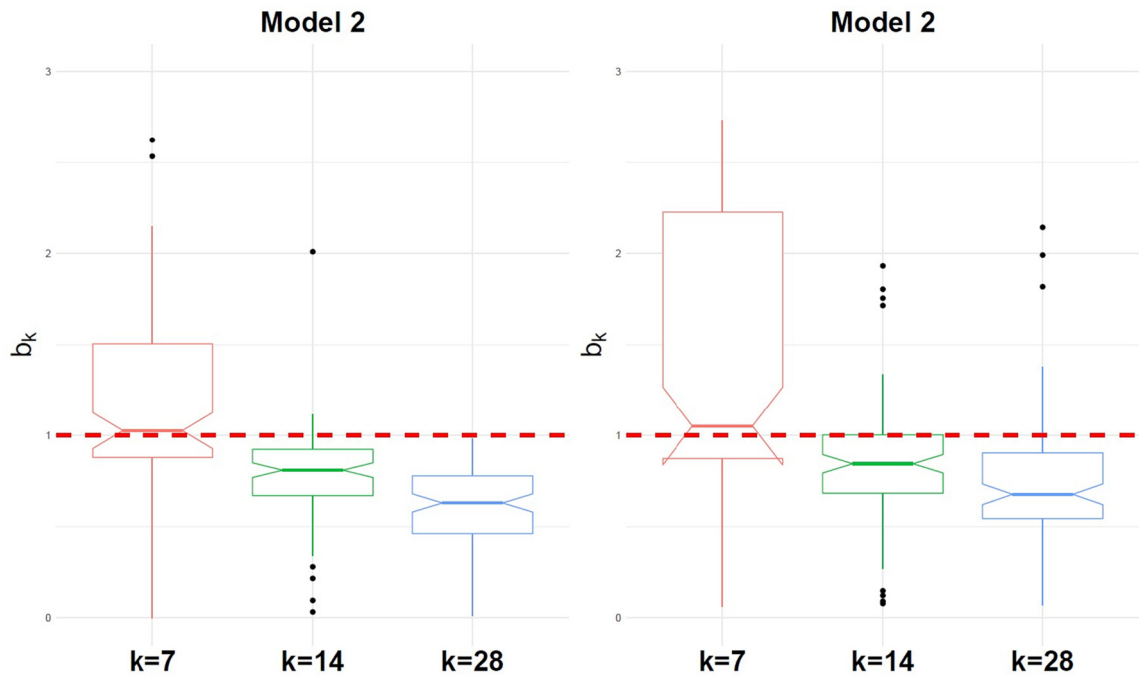


Fig. 4. Estimated  $b_k$  coefficients, in the pre-Covid-19 (left) and the Covid-19 periods.

market across high/low seasonality and thus a more accurate estimation of the parameters  $b_k$  is obtained. The case  $k = 7$  is paradigmatic, as the  $b_k$  coefficients concentrate around 1, signaling that as the day of the stay approaches, hotels expect market conditions to be very similar to those that will be encountered at the last-minute. In our opinion, the above findings provide further evidence of the effectiveness of the score-driven approach for modeling dynamic pricing strategies based on data scraped from OTAs.

As a relevant seasonality pattern in Milan is that driven by midweek and weekends, we perform an ex-post empirical analysis showing how price shocks (occurring when the last-minute demand does not meet the hoteliers' expectations) vary between

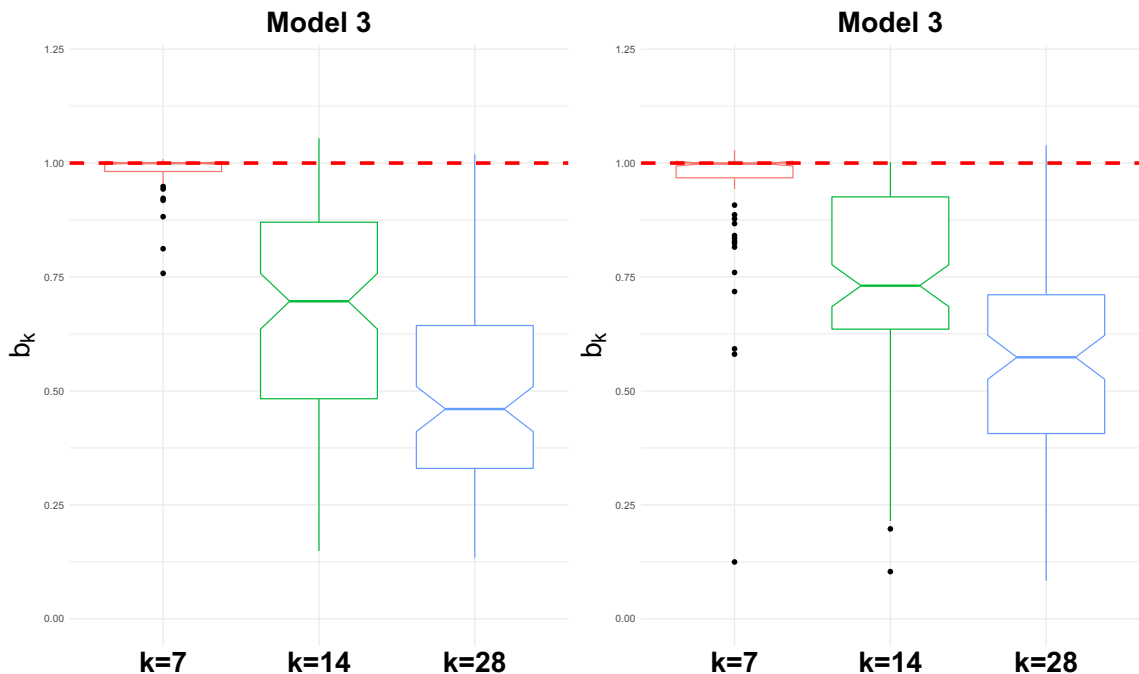


Fig. 5. Estimated  $b_k$  coefficients, in the pre-Covid-19 (left) and the Covid-19 periods.

**Table 2**  
Model 3, last minute adjustment  $\varepsilon_{t, k}$  averaged across hotel and time dimensions.

	$k = 7$		$k = 14$		$k = 28$	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Pre-Covid-19						
Midweek days	1.5	7.7	55.1	23.8	85.1	32.5
Weekends	3.9	10.6	61.5	31.5	94.9	41.3
Total	2.2	8.7	56.9	26.4	87.9	35.5
During-Covid-19						
Midweek days	22.6	20.7	62.5	24.6	85.6	28.6
Weekends	21.7	19.2	65.2	27.2	89.3	29.8
Total	22.3	20.3	63.3	25.4	86.6	29.0

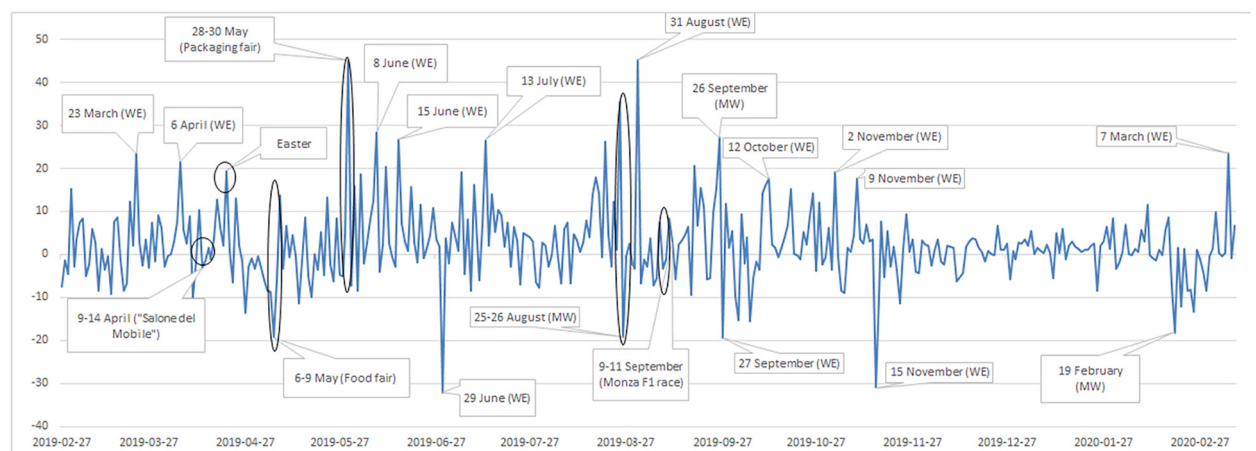
midweek days and weekends. Results are reported in Table 2. We define midweek days from Sunday to Thursday, and weekend as Friday and Saturday.

We note that last-minute adjustment, not proportional to price, is higher in the weekends. The gap between weekends and midweek days reduces as the advance booking decreases, reaching its minimum for  $k = 7$ . Moreover, the variability of the last-minute adjustment declines too, signaling that at higher  $k$  hoteliers are less homogeneous in choosing the last minute strategy. Finally, averages and variability patterns are similar between the pre-Covid-19 and Covid-19 and periods, except for at  $k = 7$ . The higher last-minute adjustment and variability observed during the Covid-19 period confirm that the last-minute tactics not proportional to the price in  $k = 7$  have become more important.

In the following, we deepen the analysis for  $k = 7$  showing the seasonal dynamic of the last-minute adjustment averaged only across hotels (see Figs. 6 and 7).

In the pre-Covid-19 period, see Fig. 6, the days when extreme  $\varepsilon_{t, 7}$  occur are more frequently weekends, which signals a greater difficulty to predict the pick-up curve in periods of low demand. Accordingly, it is interesting to observe that during the weekend of the Monza F1 Grand Prix or during the (probably) most important fair in Milan (the “Salone del Mobile”z wooden furniture and design exhibition) last-minute price adjustments have been rather small. By contrast, we find that hoteliers have practiced high last-minute discounts/surcharges in correspondence of fairs related to other major Italian industries such as packaging and food. This evidence indicates that the hoteliers' expectations regarding the demand were not satisfied at the last minute. More in general, the months of March, May, September, and October (traditionally devoted to exhibitions) show the most variable patterns in the last-minute adjustment. We may also see a great uncertainty in holyday periods (Easter and mid-August Assumption week), when unpredictable last-minute factors such as weather conditions play a major role in affecting last-minute reservations/cancellations.

During the Covid-19 period, see Fig. 7, the last-minute adjustment is high and positive across all the lockdown time, reaching its maximum peak on March the 17th (exactly  $k = 7$  days after the beginning of the lockdown). Moreover, always during the lockdown the  $\varepsilon_{t, 7}$  shows an overall negative trend which is consistent with the fact that hoteliers learned how to fix prices in time of mobility restrictions. In addition, the strong competition on last-minute demand spans a time interval that extends also beyond the end of the lockdown. Finally, we note that the pandemic has modified the last-minute competition pattern, as most of the  $\varepsilon_{t, 7}$  peaks do no longer occur in correspondence of weekends, confirming that the restart of the MICE segment, after the end of the lockdown have not restored the usual level of demand in the city.



**Fig. 6.** Pre-Covid-19 last minute adjustment  $\varepsilon_{t, 7}$  averaged across hotels.

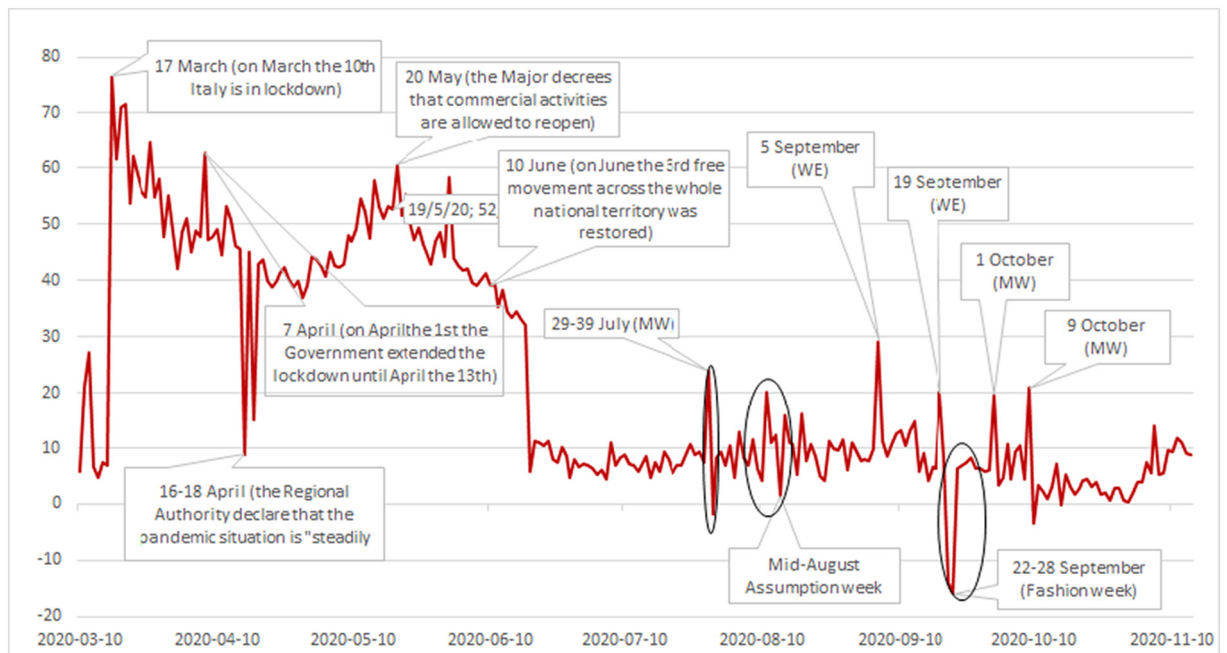


Fig. 7. During Covid-19 last minute adjustment  $\varepsilon_{t,7}$  averaged across hotel.

## Implications and conclusions

Covid-19 is the worst disaster affecting the hospitality industry in many years, and remains an under-investigated topic. It put the three main official surveys monitoring tourism (UNWTO, 2008) to the test, highlighting their limitations in terms of timeliness (Aroca et al., 2017). Consequently, the public debate has developed primarily around general impressions and data provided by several of the stakeholders hit by the crisis, while the academic debate has centered on the digital footprints left by tourists and tour operators in the form of user-generated content. Supply-side information, appearing on the OTAs, is also expected to reflect what is going on in the accommodation industry (Guizzardi et al., 2021). Thus, appropriate quantitative approaches can better exploit the informative potential of the “big data” from the Internet, providing deeper insight on whether/how tourists and operators have changed their behavior during the pandemic.

### Theoretical implications

We propose a theoretical framework to model persistence of hotel rates across the calendar time and during the advance booking based on information that managers regularly post on-line. The tourism demand is complex and unpredictable enough to question the normality assumption commonly employed in inter-temporal dynamic pricing studies (Abrate et al., 2019). Therefore, in the present paper we analyze the (stochastic) behavior of last-minute price shocks using a non-Gaussian framework that allows us to better cope with the dynamic of demand peak loads (see Dana (1999)). In doing so, we show that the kurtosis and symmetry parameters of the price shock distribution are very different from those of a normally distributed variable.

Our statistical approach is underpinned by both capacity and time-based theories, see Alderighi et al. (2015). However, it also explicitly accounts for stochastic reservations/cancellations, as suggested by the more and more popular pricing algorithms that employ stochastic demand functions (Talluri & van Ryzin, 2005).

We develop an economic model in which hotels fix the prices at the different advance bookings based on their own expectations about both the demand and the consumers' price elasticity, as well as on the differences between the planned pick-up curve and the realized sales (inventory management). In doing so, we are also able to capture the intertwined dynamics between seasonal shocks in prices and quantities (as suggested by Lozano et al. (2021)), even though we do not observe the latter directly.

Our theoretical model translates into a statistical specification for the “expected” last-minute price, where the parameters (mean, variability, symmetry, and kurtosis) depend on both the advance booking and the arrival day  $t$  (seasonality), while the price posted in  $t - k$  is regarded as an explanatory variable summarizing the decision-makers expectations about the market conditions and the inventory management. For each advance booking, we propose employing a skewed and fat-tailed distribution to cope with the price asymmetry and the extreme last-minute price corrections widely documented in the literature (Abrate et al., 2012; Kim et al., 2009; Mohammed et al., 2021).

In particular, to account for possible dynamic effects in the parameters of the distribution of the last-minute price shocks, we employ a dynamic score-driven skew- $t$  approach, which is totally new in the field of dynamic pricing. Results show that the



goodness-of-fit obtained relaxing the hypothesis of normality (Model 2) is significantly higher than that of a standard OLS regression (Model 1). Moreover, allowing for dynamic parameters in the skew-t distribution (Model 3), we can fully and conveniently exploit the information contained in the last-minute price shocks, as the Akaike criterion improves further.

#### *Practical implications: a focus on Covid-19*

In line with other studies (see, e.g., [Matsuura and Saito \(2022\)](#)), we find that during the pandemic hotels have pursued price-discount strategies. However, the mobility restrictions caused by Covid-19 have reduced the highest prices charged by hotels by approximately 17%, while minimum rates do not show significant variations, despite the increase in marginal costs due to Covid-19 safety measures. The disappearance of the MICE and leisure segments has reduced the average advance booking, which in turn has raised the importance of last-minute tactics and has changed the direction of the price path across the booking window. During the Covid-19 period, the average price is higher at the last minute than at the early booking, whereas, before Covid-19, it was lower.

Most of the travels (regardless of demand segment) were booked within the last 7 days, due to unforecastable government restrictions and safety concerns. Therefore, the importance of advance booking as a lever for dynamic pricing and inventory control has declined, which, as shown by [Webb et al. \(2021\)](#), is detrimental to the accuracy of revenue management forecasting algorithms. Accordingly, as pointed out by our empirical analysis, last-minute price adjustments have become more and more crucial. This is especially true during the initial lockdown, when last-minute shocks are always positive and higher than before the Covid-19, even though they also show an overall negative trend as hoteliers learned how to fix prices in time of mobility restrictions.

The pandemic has also reduced and modified the impact of seasonality on pricing strategies. The extreme surcharges/discounts have become less heterogeneous among hotels, especially at the last minute. However, a few hotels show a price distribution with a negative skewness (a prevalence of prices higher than the average), mainly at the longest advance bookings. This might reflect the goal of maintaining Internet visibility while managing to stay closed on certain days, to save on personnel, heating and electricity costs or the fact that some hotels find themselves in a transient competitive advantage because they have already complied with the latest health and safety protocols. In the pre-Covid-19, extreme last-minute price adjustments occur mainly at weekends, which signals the difficulty to predict the pick-up curve in periods of low demand. Similarly, we also see frequent high last-minute shocks in holiday periods, when unpredictable factors such as weather conditions play a major role in affecting last-minute reservations/cancellations. However, in the Covid-19 period, the peaks in the last-minute shocks do no longer occur in correspondence of weekends, consistently with the fact that on midweek days the tourism demand has not completely been restored, despite the restart of the MICE segment after the end of lockdown.

Finally, as we leverage public data, our model is capable of unveiling the competitors' expectations about the future behavior of the market (demand). Specifically, our dynamic model can be utilized to identify or study how a hotel is positioned on the market, by simply assuming that its inter-temporal price discrimination policy is driven by the degree of patience and the nature of customers ([Abrate et al., 2012](#)), as business travelers tend to plan their journey later and are more price inelastic than leisure travelers.

In particular, since the coefficient  $b_k$  (which multiplies the price posted  $k$  days in advance) is inversely proportional to the "relative strength" of the market conditions in  $t$  expected at time  $t - k$  (size of potential demand and price elasticity), the lowest value of  $b_k$  identifies the advance booking (i.e., the market segment) where hotels expect to carve out a position in a competitive business environment.

#### *Further developments and limitations*

The proposed analysis could be made even more general by considering the relationship between the prices at any two different advance bookings. This would not require substantial theoretical and interpretative modifications, since one would simply have to replace the dependent variable  $P_{t,0}$  with the price at the advance booking of interest. The investigation could be conducted focusing on a single hotel in order to learn (from publicly available data) how it manages dynamic pricing. For example, instead of considering the pre-Covid-19 and the Covid-19 periods, one could compare two intervals of time before and after a structural upgrade or a management change, to study how the event has modified the hotel's pricing practices and/or market positioning. In this way, the proposed evaluation framework would be used as a management control tool to monitor (ex-post) the effectiveness of pricing policies.

We acknowledge that the quantitative approach developed in this paper can only be applied to accommodation structures that regularly publish prices online and that it requires a data collection process, as - to date - there is no historical repository of hotel rates.

We also acknowledge that the fact that some of the non-refundable rates are missing may introduce some bias, which constitutes another limitation of our analysis. Moreover, when transforming refundable rates into non-refundable ones through auxiliary regressions, we could relax the (implicit) assumption that the relation between the rates is not affected by the Covid-19.

Finally, we have not considered factors such as the position on the booking.com search page and the hotel rating, which instead could be considered to better explain pricing choices.

#### **CRedit authorship contribution statement**

**Guizzardi Andrea:** Conceptualization, Methodology, Software, Supervision, Validation, Formal Analysis, Data curation, Writing.

**Ballestra Luca Vincenzo:** Methodology, Supervision, Validation, Formal analysis, Writing.

**D'Innocenzo Enzo:** Methodology, Software, Formal analysis, Writing.

## Data availability

Data will be made available on request but only for research purposes (we have not permission to use data for commercial purposes)

## Declaration of competing interest

I notify that there's no financial/personal interest or belief that could affect the authors' objectivity. There are no competing interests to declare.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.annals.2022.103495>.

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**Andrea Guizzardi** leads the Center for Advanced Studies in Tourism of the University of Bologna. His research is related to dynamic pricing and quantitative analysis of tourism demand/supply.

**Luca Vincenzo Ballestra** is a Professor of Mathematics for Economics at the University of Bologna His research is focused on mathematical and statistical methods for economics and finance.

**Enzo D'Innocenzo** is post-doc researcher in Econometrics at Vrije Universiteit Amsterdam. His research is related to time series analysis and statistical inference.