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ORIGINAL PAPER

Reverse engineering the last-minute on-line pricing practices: an application to hotels

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Abstract

We suggest a nonlinear time series methodology to model the (last-minute) price adjustments that hotels active in the online market make to adapt their early-booking rates in response to unpredictable fluctuations in demand. We use this approach to reverse-engineer the pricing strategies of six hotels in Milan, Italy, each with different features and services. The results reveal that the hotels' ability to align last-minute adjustments with early-booking decisions and account for stochastic demand seasonality varies depending on factors such as size, star rating, and brand affiliation. As a primary empirical finding, we show that the autocorrelations of the first four moments of the last-minute price adjustment can be used to gain crucial insights into the hoteliers' pricing strategies. Scaling up this approach has the potential to equip policymakers in smart destinations with a reliable and transparent tool for the real-time monitoring of demand dynamics.

Keywords Management strategy assessment · Web-based shared knowledge · Revenue managemenet · Last-minute price adjustment · Non-deterministic seasonality

1 Introduction

Online dynamic pricing has become a common marketing-management practice in many industries and the accommodation sector was a pioneer in this field. Over the past few decades, the diffusion of Online Travel Agencies (OTAs) has made dynamic pricing strategies, if not transparent, at least understandable through analyses of public and easy-to-collect data. The potential of this data, as a source

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of shared knowledge, has not yet been fully exploited, see Buono et al. (2017). In the present paper, we show that it is possible to investigate important managerial aspects of the accommodation industry, or any other sector with strong online sales, with an original application of statistical methodologies routinely employed in other research fields. Specifically, we propose a statistical approach that, by observing the prices hoteliers post online over time, allows us to "objectively" evaluate the mechanism accommodation structures utilize to enact their dynamic pricing techniques. In particular, we can determine if and how the stochastic demand and the hoteliers' early-booking pricing decisions (price discrimination strategies) affect their last-minute price adjustments. Following the literature on dynamic pricing (e.g., Weatherford and Kimes 2003), we consider the price adjustments at different advance bookings as the price shocks necessary to cope with unexpected reservations/cancellations in the booking window. We study the evolution of these shocks over the calendar days. We regard them as the realization of a stochastic process, and model the moments of its probability distribution as time-varying, in line with the assumption that dynamic pricing practices are also affected by seasonality. In particular, we focus on the dynamics of location (the size of the price adjustment), scale (the variability), symmetry (the prevalence of either discounts or price increases), and kurtosis (the relative frequency of extreme adjustments). That way, we can disentangle (i.e., reverse-engineer) pricing decisions of hotels active in the online market, obtaining relevant insight into the managers' propensity to rely on dynamic pricing and their ability to manage stochastic demand fluctuation. We model the time-varying (conditional) probability distribution of the price shocks based on the literature on non-Gaussian dependence that has become very popular in the field of finance. Precisely, we dynamically specify the location, volatility, kurtosis, and skewness of the last minute adjustment using a score-driven model [see, for example Harvey (2013)]. As Creal et al. (2011) pointed out, the use of the conditional score for updating the dynamic parameters is very intuitive. This approach updates them at each point in time via a (possibly scaled) steepest ascent step to improve the expected fit to the postulated skew Student's t distribution. Analogously to the popular GARCH models, where the conditional variance of the returns is time-varying and follows an updating function driven by the squared-returns, we model the time-varying parameters of the price error by an updating function that takes as innovation term the score of the conditional likelihood, that is, the derivative of the (postulated) conditional log-density of the error term. Furthermore, we consider the fat-tailed and (possibly) skewed nature of the price error distribution by specifying a dynamic skew Student's t distribution with time-varying parameters. In this respect, an alternative approach for modelling the possible fat tailed distribution of the last minute adjustments could also be provided by a Gaussian innovation process with jumps, as considered in Ballestra et al. (2023).

We believe that such an approach can be employed in all the industries where goods/services are not necessarily consumed on the day of purchase and capacity is fixed (e.g., tickets for events, overnight stays, seats in means of transportation) to detect, at the business-unit level, the presence of systematic bias in the mechanism through which on-line prices are dynamically updated. For instance, by focusing on the dynamics of the kurtosis, we can assess how the probability of observing extreme price shocks is persistent over the calendar days. We present an empirical analysis focusing on the business city of Milan (Italy), a highly competitive place where revenue management algorithms are widely used. We select six accommodation structures belonging to different market segments, each having distinctive features. These hotels are natural candidates for our data-driven assessment since they also regularly published prices during the Covid-19 pandemic. However, we note that these six hotels are considered for illustrative purposes. Indeed, one can apply the methodology we propose to any (single) hotel in any city that regularly posts prices online. Policymakers can utilize this approach to monitor daily tourism seasonality dynamics at any territorial level, provided sufficient hotels in an area publish rates on the OTA. For instance, if autocorrelations in the location parameter (of a set of hotels located in a ZIP code) are low during a certain event, it can be inferred that the event does not meet operators' expectations, signalling short-term fluctuations of the last-minute price adjustments. Thus, policy makers are informed about undertourism or overtourism effects in real-time (i.e., if the event has had more or less success in terms of tourist arrivals than expected based on their experience). From a managerial perspective, our quantitative methodology can be regarded as a tool that hotel managers can use to assess the pricing strategies of their own hotels or competitors after gathering the necessary pricing information. By modeling the four parameters mentioned above with an autoregressive specification of order one (allowing them to vary over time), we can account for the stochastic effects of seasonality (demand fluctuations) on pricing practices. For example, when the autoregressive coefficient of the location parameter is close to one, last-minute price adjustments tend to persist across consecutive days. This indicates that the hotel applies last-minute surcharges/discounts according to an extremely persistent pattern that do not change with fairs or weekends. To the best of our knowledge, this approach is original compared to the existing literature, as we are the first to suggest how to utilize upstream pricing schemes to obtain simultaneously high-quality third-party information on size, symmetry, volatility and probability of extreme last-minute adjustments. The remainder of the paper is structured as follows: In Sect. 2, we review the existing literature; in Sect. 3, we describe the dataset and the theoretical framework employed; in Sect. 4, we present and discuss the results obtained. Finally, Sect. 5 concludes.

2 Literature review

Although the interest of scholars and operators in revenue management (RM) was initially aimed at improving the performance of accommodation structures (Kimes 1989), more recent literature agrees that dynamic pricing policies that maximize revenues can also be beneficial to customers [at least, when the demand elasticity ranges over a small interval, see Chen and Gallego (2019)]. Demand forecasting is the core of the pricing algorithms. The simple time series models (e.g., the exponential smoothing) that were initially used to predict the demand at a given arrival day have given way to techniques based on empirical booking curves (Zakhary et al. 2008) and, more recently, to stochastic demand modeling (Lee 2018). These more recent approaches are the closest to the discreteness of consumer choices (Talluri 2004, p. 329), allowing hotel managers to jointly optimize assortment and prices. Nowadays, fine-tuning the menu of prices and service times allows hotels to dynamically manage demand-capacity imbalances even using personalized demand approaches that combine discrete choice modeling with a data-driven identification of customer segments based on guest characteristics, booking attributes, and room features (Cho et al. 2022). Strategic idleness (deliberately rejecting incoming requests for discrimination) and late service prioritization or rejection (rationing capacity or clearing the queue for delayed customers), have also been considered to determine the optimal pricing policy (Abhishek et al. 2021). Hence, personalized pricing (Chen and Chen 2015) and discrete choice demand models, which can better capture the mechanism of customer decision making (also taking into account unobservable no-purchase incidents, see Li and Talluri (2020), have gained increasing attention from academics and practitioners (Berbeglia et al. 2022). With the diffusion of online bookings, prices have become transparent, and online search engines allow researchers to observe pricing behaviours. In spite of all the recent theoretical advancements and the capabilities offered by growing computational algorithms, the empirical analysis of the revenue managers' pricing behavior is still underdeveloped. Abrate et al. (2012) were among the first to analyze the dynamics of hotel prices across the booking horizon. This is not a simple task because, as was clearly understood from the beginning, the mathematical techniques and the variables used to model the pricing strategies should consider the nonlinearity in the relationship between price and performance (Schwartz and Chen 2010), as well as a large number of other conditioning factors. For example: hotel characteristics and the many possibilities they have to differentiate their product (Abrate and Viglia 2016), competition among neighborhoods (Guizzardi et al. 2019) and with other segments of the lodging market (Dogru et al. 2020), or spillovers from competition in the airline or other industries (Forbes and Kosová 2022). Other relevant factors are the reference prices that consumers form based on their past pricing choices/observations (Choi and Mattila 2018) and the interplay between obfuscation and prominence on OTAs (Mamadehussene 2020). We expect that all the above variables have a persistent effect on pricing decisions, modulated by both the daily seasonality that influences the demand (Sainaghi and Mauri 2018) and the pick-up curve forecasted and observed by the hoteliers (Ivanov and Zhechev 2012; Webb 2016). Unfortunately, the utilization capacity at different advance bookings and arrival days is not publicly available. In the absence of direct access to property management system data, scholars have proxied daily occupation rates by the number of hotels selling rooms online or by the number of rooms offered [see, among others, Abrate et al. (2012)]. These measures can be highly biased for hotels with multi-channel distribution systems, and thus we suggest an alternative approach based on the correlation between price and quantity. In particular, we consider the published rates to be informative for the unobserved pick-up curve. In fact, prices are the revenue managers' subjective synthesis of the interaction between all the hotels' physical and reputation characteristics and the observed and expected market conditions, namely, the expected size of the demand for a stay on day t and the price for that stay published on day $t-k$, i.e., k days in advance. It is not a coincidence that (when considered) the price published on day $t-1$ is the most important explanatory variable in hedonic pricing models (Soler et al. 2019). Price (auto)correlation is also important to model the pricing behavior in the booking window. Mohammed et al. (2021) highlight that rate changes in the last minute booking window depend on the price at the beginning of the week (a proxy of the current inventory). For this reason, we suggest using the published prices to reverse-engineer the dynamic pricing mechanism followed by hoteliers. Moreover, the literature has clearly stated the importance of price volatility, pointing out the possible asymmetric relation between pick-up curve and pricing. Area-specific or even macro events can induce temporary peaks in the price volatility, which can be modeled using GARCH approaches, see Chan et al. (2005). Abrate et al. (2019) suggest focusing on the variability (and median) of the prices during the advance booking to explain how hotels maximize revenues. A further interest in the dynamics of price volatility stems from the importance of price stability when customers form their internal reference rates (see—among others—Viglia et al. (2016), and Choi and Mattila (2018) or from the need to prevent speculative behaviors of canceling and re-booking (Gorin et al. 2012). More recent studies also point out the presence of asymmetries in pricing decisions. For example, Mitra (2020) shows that hotels reduce prices at a steeper rate when faced with reduced demand compared to the case of demand increase, whereas Mohammed et al. (2020) highlight some degree of asymmetry between upward and downward movements (caused by unforeseen reservations/cancellations). However, to the best of our knowledge, no scholars have ever considered the dynamics of higher order moments such as—for example—the kurtosis. It is also interesting to investigate the effect of extreme demand shocks on the price and—above all—to assess if (and how) the first four moments of the distribution of the price adjustments exhibit a time-varying pattern, e.g., if these moments vary according to a seasonality pattern. We suggest modeling the time-varying parameters of the probability distribution of last-minute price adjustments using a score-driven methodology (Blasques et al. 2018). Even though most of the score-driven applications developed so far are in the macroeconomy and finance areas, remarkable works also exist where score-driven models are used in other contexts. For example, some scholars have applied them to sports, to predict results in tennis (Gorgi et al. 2019) or football matches (Koopman and Lit 2019). Furthermore, the score-driven approach has recently been employed by Hansen and Schmidtblaicher (2021) to predict the probability of success in vaccination and by Gasperoni et al. (2021) to model the brain signals recorded using functional magnetic resonance imaging. To date, we have found no other applications concerning microeconomic data except for (Guizzardi et al. 2022). The present paper attempts to fill this gap by showing that we can employ score-driven models to reverse-engineer the RM policy of any hotel that regularly publishes rates online. Thus, they could also be useful to analyze the online pricing strategies that decision-makers follow in other industries.

3 Understanding last-minute price adjustments (methodology)

Let $P_{i,t,k}$ denote the price posted by hotel i for a room booked for day t with $k \geq 0$ days in advance. That is, $P_{i,t,k}$ is the asking price at time $t - k$ for a stay on day t. We propose the following model:

$$P_{i,t,0} = \mu^*_{i,t,k} + b_{i,k}P_{i,t,k} + \eta_{i,t,0}, \tag{1}$$

where $\mu^*_{i,t,k}$ and $P_{i,t,k}$ are linear regression coefficients and $\eta_{i,t,0}$ is an error term with a (time-varying) probabilistic distribution. In Eq. (1), the last minute price $P_{i,t,0}$ is specified as the sum of three contributions well established in the literature. The parameter $\mu^*_{i,t,k}$ accounts for the time-based theory according to which hotels may apply inter-temporal price discrimination across the advance booking k. It represents the contribution to the price for a good consumed on day t decided by the manager on day $t-k$ and not proportional to the price $P_{i,t,k}$. It depends on both the inventory management (the rooms that the hotelier planned to sell at t and $t-k$) and the demand shock observed at $t-k$. Therefore, it represents an inventory-based advance booking discount/surcharge. With $b_{i,k}P_{i,t,k}$ we model the expectation that the hotelier has at time $t-k$ about the demand on day t (size and customers' price elasticity). This term may depend on both the demand expected for day t and the demand observed on day $t-k$, even though, for the sake of simplicity, we assume $b_{i,k}$ only depends on k. Thus, $P_{i,t,k}$ summarizes the whole information set that the RM system could use (at time $t-k$) to determine the right price for a given room at the last minute ($P_{i,t,0}$). This is a potentially very large information set that encompasses expectations about market seasonality, weather, pandemics and geo-political events. In addition, it includes factors that could affect the rates on day t which were not predicted by the revenue manager at time $t-k$, as they are time-invariant or known, namely: the value of the property, the hotel location, the number of competitors, the occupation rate (observed on day $t-k$) or the features of the room offered (view, floor, quality of the furnishings). Consequently, $b_{i,k}$ measures the strength and the uncertainty of the market conditions that the hotelier expects k days in advance (Guizzardi et al. 2017; Mohammed et al. 2020). Its value is greater than 1 when at $t-k$ the manager is confident that current market conditions are less favorable than they will be at the last minute. On the contrary $b_{i,k} < 1$ indicates that the hotelier is systematically afraid the hotel will not be competitive in the last minute period, so tends to set higher prices at $t-k$ in order maximize the revenue in the early booking period. The third contribution, $\eta_{i,t,0}$, represents the departure of the price posted at t from $b_{i,k}P_{i,t,k}$ due to the shocks that may affect the demand in the time interval from $t-k$ to t. We can consider this as determined by a "pure" forecasting error (i.e., at time $t-k$ the manager might not correctly forecast the occupancy rate for day t). For the sake of brevity, from now on we drop the subscript i and we consider the following error term:

$$\epsilon_{t,k} = \mu^*_{t,k} + \eta_{t,0}, \tag{2}$$

so that, according to (1),

$$P_{t,0} = b_k P_{t,k} + \epsilon_{t,k}. \tag{3}$$

The random component $\epsilon_{t,k}$ is the core of our reverse-engineering approach. It represents the (stochastic) last-minute price adjustment implied by the pricing strategy pursued by the manager at time $t-k$. We can think of this (last-minute) price shock as the departures from the pick-up rates planned/forecasted along the booking window—i.e., the demand shocks in the window [0, k]. In particular, we focus on the first four moments of its probability distribution of $\epsilon_{t,k}$. The location $\mu_{t,k}$ represents the modal value of the last minute price adjustment. The scale $\varphi_{t,k}$ provides information about the dispersion of the shock around the location. The skewness $\gamma_{t,k}$ determines whether price adjustments are more likely to be positive or negative, i.e., if they occur due to unexpected reservations rather than cancellations. Finally, the kurtosis, measured by the degrees of freedom $v_{t,k}$, provides information about the probability of observing extreme relative price adjustments in the advance booking window [0, k]. By modeling the above four parameters with an autoregressive specification of order one (i.e., by letting them vary with time), we can account for the (stochastic) effects of seasonality on pricing practices. For example, when the autoregressive coefficient of the location parameter is close to one, the last minute price adjustments tend to persist across consecutive days. This signals that the hotel applies last-minute surcharges/discounts according to extremely persistent path, i.e., a monthly or an even higher seasonality. In other words, it does not apply last-minute adjustments that change with fairs or weekends. Thus, in this paper, we propose to reverse-engineer the dynamic pricing strategies adopted by hotels by analyzing sizes andautocorrelations of location, scale, kurtosis, and skewness of the stochastic last-minute adjustment. Such an approach provides an objective criterion to assess the performance of RM systems based only on information publicly available on the Internet and consolidated and transparent statistical tools. An autocorrelation close to one suggests a high persistence (a cyclical behaviour) in the considered moment, i.e., an increase/decrease of the moment is often followed by another increase/decrease). It denotes a cyclical pattern calling for the predominance of long term pricing strategies on short term price tactics. If autocorrelations are high, hotels are likely to modify the posted rate accordingly to a smooth pattern (i.e., monthly or longer) that is not affected (or more likely it does not react promptly) to short term demand shocks. In the limit case of weak non-stationarity (autocorrelation equal to one) we have a perfect time dependence, so that we expect a very slow mean reverting pattern in the moment of the last-minute price adjustment (location scale skewness or kurtosis have very persistent dynamics). In particular, we suggest the assessment rules listed below.

1. Location (the “mean” of $\epsilon_{t,k}$). High average values of the last-minute shock not proportional to early booking prices imply that the hotelier relies heavily on last-minute tactics based on inventory management and/or is not able to forecast last-minute demand (applying high last-minute discounts/surcharges). Large values of autocorrelation (close to one) indicate that the RM system does not differentiate last-minute discounts or surcharges with respect to intra-week negative or positive demand peaks (a behavior suggested by a small positive autocorrelation). A high negative autocorrelation is the worst-case scenario because it implies that last-minute price adjustments are inconsistent with any seasonal fluctuations and/or implies that managers are not fixing early booking prices in accordance with last-minute pricing policies.
2. Scale (proportional to the standard deviation of $\epsilon_{t,k}$). A low value implies that the probability of observing last-minute discounts/surcharges different from the

location is small (i.e., the RM system always accurately predicts the last-minute market, setting early booking prices consistent with the last-minute one). Furthermore, a small scale is also desirable for the sake of consumer price fairness issues. Large values of autocorrelation (close to one) indicates that uncertainty remains smooth across different seasons (i.e., last-minute adjustments are uniform across different seasons t). By contrast, a small autocorrelation implies discounts/surcharges consistent with an intra-week interplay of low and high-demand periods. During the high season, the hoteliers are less fearful of not selling all the rooms, and thus the standard deviation of the shock is smaller than in the adjacent low demand days.

3. Kurtosis (the probability of observing extreme $\epsilon_{t,k}$). A high level of kurtosis suggests a high propension towards last-minute pricing tactics or a low accuracy in forecasting the pick-up curve. For example, extreme last-minute surcharges/discounts are offered in cases of a shortage/excess in available rooms (or simply to communicate a high price to possible walk-in guests). A high degree of autocorrelation highlights that the RM system maintains a similar accuracy in forecasting the pick-up curve over the calendar day t. However, it could also reflect the manager's preference for fixing early booking prices that systematically leads to under/over selling rooms in the early booking period.
4. Skewness (the lack of symmetry in $\epsilon_{t,k}$). A value much higher/lower than zero implies that the probability of observing a discount relative to the average last-minute price adjustment is higher/lower than the probability of a surcharge. If the skewness has a large degree of autocorrelation, the RM system is not efficiently managing incoming reservations/cancellations. In fact, if the last-minute shock is higher/lower than its mean for several consecutive values of t, then the RM system is systematically biased (i.e., it is more accurate in forecasting incoming reservations then cancellations over long time intervals, or vice versa).

Provided that the pricing scheme is applied for every t, we argue that the above points represent four interpretative keys to reading the dynamics of the parameters of the error distribution, which leads us to an automatic assessment of the effectiveness of the RM system. In the following subsections, we present the three stochastic models that we will estimate and compare in our empirical application. For this purpose, let $p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k)$ denote the conditional probability density function of the price shock, where $\mathcal{F}^k_{t-1} = \sigma\{\epsilon_{t-1,k}, \epsilon_{t-2,k}, \dots\}$ is the filtration generated by $\{\epsilon_{t,k}\}$ and $\boldsymbol{\vartheta}_k$ is the vector of unknown parameters of the conditional density. Depending on which of the three models we consider, $\boldsymbol{\vartheta}_k$ will vary accordingly.

3.1 Models for non seasonal last-minute price adjustment

Let us introduce the two static models we use as benchmarks for our dynamic analysis. As a first step, we assume that $\epsilon_{t,k}$ is normally distributed with location (mean) μ_k and scale (standard deviation) $\varphi_k \in \mathbb{R}^+$. Thus we set $p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k) = \mathcal{N}(\mu_k, \varphi_k^2)$ and $\boldsymbol{\vartheta}_k = (\mu_k, \varphi_k)^\top$. This assumption is very commonly used in the management literature.

However, a more realistic alternative is to use a skew-t distribution, to account for the possible asymmetry and the high kurtosis of the price shock highlighted (for example) by Hung et al. (2010) and Guo et al. (2021)). Therefore, following Fernandez and Steel (1998) and Azzalini (2013), we model $\epsilon_{t,k}$ also by a static skew-t distribution with $\nu_k \in (1, +\infty)$ degrees of freedom and skewness parameter $\gamma_k \in \mathbb{R}^+$, i.e., $p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k) = Skew\text{-}t(\mu_k, \varphi^2_k, \nu_k, \gamma_k)$, and $\boldsymbol{\vartheta}_k = (\mu_k, \varphi^2_k, \nu_k, \gamma_k)^\top$. Note that the constraint $\nu_k > 1$ is imposed to ensure that $\mathbb{E}[\epsilon_{t,k}] < \infty$. The resulting models are labeled as:

$$\textbf{Model 1} \;: \qquad P_{t,0} = b_k P_{t,k} + \epsilon_{t,k}, \qquad \epsilon_{t,k} \overset{IID}{\sim} \mathcal{N}(\mu_k, \varphi^2_k), \tag{4}$$

$$\textbf{Model 2} \;: \qquad P_{t,0} = b_k P_{t,k} + \epsilon_{t,k}, \qquad \epsilon_{t,k} \overset{IID}{\sim} Skew\text{-}t(\mu_k, \varphi^2_k, \nu_k, \gamma_k). \tag{5}$$

3.2 A model for seasonal last-minute price adjustment

The above specifications assume that the shape of $\epsilon_{t,k}$ does not depend on the arrival day t (but only on the chosen advance booking k). However, we expect that the pricing decisions of hotels are strongly influenced by seasonality, whose pattern can also be very complex (with different periodicity), especially at a daily observation frequency and in large metropolitan areas characterized by both leisure and business tourism. Therefore, we let the parameters of the distribution of $\epsilon_{t,k}$, (i.e., the location $\mu_{t,k}$, the scale $\varphi_{t,k}$, the degrees of freedom $\nu_{t,k}$, and the asymmetry $\gamma_{t,k}$) to be time-dependent and we model them using a score-driven approach. Accordingly, we specify each parameter by 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 order one. Specifically, we consider the following model:

$$Model3 \;: \qquad P_{t,0} = b_k P_{t,k} + \epsilon_{t,k}, \qquad \epsilon_t|\mathcal{F}_{t-1} \sim Skew\text{-}t\,(\mu_{t,k}, \varphi^2_{t,k}, \nu_{t,k}, \gamma_{t,k}). \tag{6}$$

The parameters $\varphi_{t,k}$ and $\gamma_{t,k}$ must take positive values, whereas $\nu_{t,k}$ must be greater than one. Thus, we transform $\varphi_{t,k}$ and $\gamma_{t,k} \in \mathbb{R}_+$, with the exponential link functions $\varphi_{t,k} = \exp\{\lambda_{t,k}\}$ and $\gamma_{t,k} = \exp\{\xi_{t,k}\}$, where $\lambda_{t,k}, \xi_{t,k} \in \mathbb{R}$. Moreover, for the degrees of freedom $\nu_{t,k}$, we opt for the transformation $\nu_{t,k} = 1 + \exp\{\psi_{t,k}\}$, where $\psi_{t,k} \in \mathbb{R}$. Therefore, we consider the change of variables

$$\boldsymbol{\Lambda}(\boldsymbol{f}_{t,k}) = \begin{bmatrix} \mu_{t,k} \\ \exp\{\lambda_{t,k}\} \\ 1 + \exp\{\psi_{t,k}\} \\ \exp\{\xi_{t,k}\} \end{bmatrix}, \tag{7}$$

where $\boldsymbol{f}_{t,k} = (\mu_{t,k}, \lambda_{t,k}, \psi_{t,k}, \xi_{t,k})^\top$. Then, according to Creal et al. (2011) and Harvey (2013), we update the distribution parameters by using the following first-order vector recursion:

$$\boldsymbol{f}_{t+1,k} = \boldsymbol{\delta}_k + \boldsymbol{\Phi}_k \boldsymbol{f}_{t,k} + \boldsymbol{K}_k \boldsymbol{s}_{t,k}, \tag{8}$$

where $\boldsymbol{s}_{t,k}$ is the unconstrained conditional scaled score, $\boldsymbol{\delta}_k = (\delta_{\mu_k}, \delta_{\lambda_k}, \delta_{\psi_k}, \delta_{\xi_k})^\top \in \mathbb{R}^4$ is a vector of intercepts, $\boldsymbol{\Phi}_k \in \mathbb{R}^{4\times4}$, and $\boldsymbol{K}_k \in \mathbb{R}^{4\times4}$ are diagonal matrices with $\mathrm{diag}\,(\boldsymbol{\Phi}_k) = (\phi_{\mu_k}, \phi_{\lambda_k}, \phi_{\psi_k}, \phi_{\xi_k})^\top$ and $\mathrm{diag}\,(\boldsymbol{K}_k) = (\kappa_{\mu_k}, \kappa_{\lambda_k}, \kappa_{\psi_k}, \kappa_{\xi_k})^\top$. Then, for *Model 3* by collecting in a vector all the static parameters, we obtain $\boldsymbol{\vartheta}_k = (\delta_{\mu_k}, \delta_{\lambda_k}, \delta_{\psi_k}, \delta_{\xi_k}, \phi_{\mu_k}, \phi_{\lambda_k}, \phi_{\psi_k}, \phi_{\xi_k}, \kappa_{\mu_k}, \kappa_{\lambda_k}, \kappa_{\psi_k}, \kappa_{\xi_k})^\top$. As a standard approach, we impose the constraints $|\phi_{\mu_k}| < 1$, $|\phi_{\lambda_k}| < 1$, $|\phi_{\psi_k}| < 1$ and $|\phi_{\xi_k}| < 1$ to keep the recursion (8) stable. The procedure to compute the unconstrained conditional scaled score $\boldsymbol{s}_{t,k}$ is analogous to that employed in Guizzardi et al. (2022) and is reported in the "Appendix".

3.3 Estimation

We estimate all the models described in the previous Subsections by maximum likelihood (ML). Besides the vector of parameters $\boldsymbol{\vartheta}_k$, we also have to estimate the parameter b_k. However, the regressor $P_{t,k}$ in (4), (5) and (6) is potentially endogenous. Endogeneity issues might occur due to missing variables since prices can also vary with the room quality, which is not fully observable based on the information gathered from the Internet. Furthermore, endogeneity issues could also occur because the last minute adjustment $\epsilon_{t,k}$ might incorporate information about the hotels' early booking occupancy, and thus it might also affect $P_{t,k}$. To handle possible endogeneity issues, we adopt the nonlinear instrumental variable (IV) approach as in Hansen et al. (2010), and accordingly perform the estimation procedure in two steps. First, we obtain a preliminary estimation $\tilde{b}_k$. In particular, for *Model 1* and *Model 2* we use a standard two-stage least squares estimator where, for each hotel, we instrument the price $P_{t,k}$ with a variable $z_{t,k}$ that we compute as the average of the prices $P_{t,k}$ posted by the other hotels For *Model 3*, $\tilde{b}_k$ is computed by standard ML. The use of the average prices published by other hotels as an instrument is not new in the literature (see Guizzardi et al. (2022)). It is worth highlighting that our experiment includes four independent hotels and two chain hotels from different hotel chains. This diverse selection of hotels, each with unique characteristics and managed by different entities, provides a crucial theoretical assurance regarding the exogeneity of the average price as an instrumental variable.

Then, we calculate the residuals $\tilde{\epsilon}_{t,k} = P_{t,0} - \tilde{b}_k P_{t,k}$, and we obtain a quasi-ML estimation of $\boldsymbol{\vartheta}_k$ as follows:

$$\tilde{\boldsymbol{\vartheta}}_k = \arg\max_{\boldsymbol{\vartheta}_k} \sum_{t=1}^{T} \ln p(\tilde{\epsilon}_{t,k} | \mathcal{F}_{t-1}^k, \boldsymbol{\vartheta}_k),$$

where T is the number of considered arrival days. Finally, following (Hansen et al. 2010), the nonlinear IV estimator of b_k is given by:

$$\hat{b}_k = \arg\min_{b_k} \frac{[\hat{g}(b_k)]^2}{\hat{\mathcal{Q}}_k},$$

where $\hat{Q}_k = \sum_{t=1}^{T} z_{t,k}^2$, and

$$\hat{g}(b_k) = \sum_{t=1}^{T} z_{t,k}\rho(P_{t,0} - b_k P_{t,k}, \tilde{\boldsymbol{\vartheta}}_k), \qquad \rho(\epsilon_{t,k}, \boldsymbol{\vartheta}_k) = \frac{\partial \ln p(\epsilon_{t,k} | \mathcal{F}_{t-1}^k, \boldsymbol{\vartheta}_k)}{\partial \epsilon_{t,k}}.$$

4 Data and results

We collected prices from booking.com for a panel of 100 hotels in the central area of Milan, Italy, from January 30, 2019, to November 11, 2020 (654 days). We excluded low and mid-segment hotels since they have a lower tendency for dynamic pricing and electronic distribution practices (Dabas and Manaktola 2007). The complete closure of the MICE segment due to Covid-19 significantly impacted tourism demand, leading to a reduction in hotels regularly posting their offers. Many hotels, including high-star ones, even closed their websites for weeks. Therefore, we concluded the data collection in November 2020. As our goal is to reverse-engineer the pricing strategies of hotels, in our micro-econometric case study we only consider 6 hotels among those with the least missing data for both the considered advance bookings (0 and 14 days), hereafter referred to as $H1, H2, \dots, H6$.

The hotels differ in star ratings, capacity, and organizational form (as shown in Table 1), thus, by looking at their pricing strategies, we can also document possible differences related to these characteristics. It's worth mentioning that the two chain hotels, $H1$ and $H6$, belong to two different chains. They are also the only accommodation structures with an internal restaurant and meeting rooms hosting more than 50 persons.

Due to space constraints, in this paper, we choose an advance booking interval of two weeks ($k = 14$) to focus on a period where the market is not characterized by a specific demand segment. In fact, at longer advance bookings, the incoming reservations are mostly made by leisure tourists, while at lower k the business segment shapes the market. Nevertheless, our analysis could be conducted for any advance booking, not only for $k = 14$. With the aid of a web-scraping software we obtain data for rooms at five different advance bookings,

Table 1 Main features of the six hotels considered

	Star rating	Rooms (class)	Organizational form	Restaurant/meeting room > 50 guest
$H1$	4	101–125	Chain	Yes
$H2$	3	51–75	Independent	No
$H3$	3	51–75	Independent	Yes
$H4$	3	26–50	Independent	No
$H5$	4	51–75	Independent	No
$H6$	4	> 125	Chain	Yes

namely, $k = 0, 1, 12, 13, 14$ days. For the last-minute price, we take the rate published online for $k = 0$ or, when not available, for $k = 1$. As the early booking price, we take the rate published online for $k = 14$ or, when not available, for $k = 13$ or $k = 12$. That way, we reduce the number of missing data while taking into account the most recent information provided by the hoteliers themselves. Since, for the first 14 arrival days in the sample, early booking prices are not available, our dataset shrinks to 640 arrival dates (starting from February 13, 2019). We scrape all the posted offers. If the scraping algorithm selects different prices for the "same" room (i.e., based only on the characteristics observed, the room appears not to be differentiated), we consider the best available rate. This choice ensures the highest homogeneity relative to possible (unobservable) product differentiation practices. The type of room most frequently offered at the last minute is a double room single use, breakfast included, and not refundable. To reduce the bias that might occur if the rooms offered at different t and k are not the same, two approaches are possible: we could either introduce exogenous dummies in the models or adjust the published price using auxiliary regressions. We prefer the latter procedure because it allows us to keep the model simple and decide whether or not to retain fitted data based on the significance of the auxiliary regressions. For instance, we estimate missing double room rates using the following linear regression in which the independent variable is the price of a single room (same i, t and k):

$$P_{i,t,k,DR} = a_{i,t,k} + b_{i,k} P_{i,t,k,SR} + \eta_{i,t,k,DR}, \tag{9}$$

where the indexes DR and SR refer to double room and single room rates, respectively. If the intercept and the slope parameter are both non-significant (at the 1% confidence level), we do not forecast the missing data. We use an analogous procedure to estimate missing not-refundable rates when refundable prices are published. In contrast, missing "meal included" rates are obtained by adding the cost of breakfast or subtracting the cost of lunch, as we note that these surcharge/discount rates are never subject to dynamic pricing (for a given hotel, they are the same for every t and k). Descriptive statistics are reported in Table 2. The average last-minute prices (averaged over t) vary widely (from 76 to 203 euros). This, however, does not affect the hoteliers' propensity to practice dynamic pricing, which always remains high, as we can see by comparing extreme quantiles.

The comparison between advance booking ($k = 0$) and early booking ($k = 14$) prices shows that only Hotel $H6$ has increasing prices—even on extreme percentiles—and a variability that does not depend on k. The pricing policies of the other five structures seem to signal greater difficulties in predicting future levels of demand (or a higher likelihood of last-minute tactics in the high/low seasons). In fact, we see a higher variability for $k = 0$, but—more noticeably—higher early booking prices in low seasons. In particular, for hotels $H1$, $H2$, $\cdots$, $H5$, the q_{10} prices are always lower at $k = 0$ than at $k = 14$, signaling the need for last-minute discounts, presumably because the prices proposed at $k = 14$ have discouraged early booking. In the case of the 3-star Hotels $H2$, $H3$ and $H4$, this last-minute discount tactic is also revealed by the large gap between the q_{10} and

Table 2 Descriptive statistics of the posted prices

	Mean		SD		q_{10}		q_{90}	
	$k=0$	$k=14$	$k=0$	$k=14$	$k=0$	$k=14$	$k=0$	$k=14$
*H*1	176.4	178.1	78.2	74.9	109.0	118.3	270.7	254.0
*H*2	97.1	91.6	52.5	42.1	52.5	68.1	161.1	122.5
*H*3	104.8	108.2	56.2	52.4	61.3	67.0	183.5	159.7
*H*4	121.0	122.6	72.4	56.7	66.0	71.6	216.2	166.8
*H*5	76.0	71.8	31.5	28.1	54.0	53.4	105.0	100.0
*H*6	203.0	176.6	85.2	85.9	134.0	110.5	313.5	266.8

Standard deviation (SD), quantiles at levels $\alpha = 10\%$ (q_{10}) and $\alpha = 90\%$ (q_{90})

the average prices for $k = 0$ (the q_{10} is always smaller than sixty percent of the average price).

4.1 Analyzing the stochastic last-minute price adjustments

In line with the objectives of this work, we analyze the probability distribution of the last-minute price adjustment. First, for the six hotels considered, we estimate *Model 1* by maximum likelihood. Results in Table 3 show that the normality assumption, which is quite common in the literature on dynamic pricing, is not supported by the data. The kurtosis is higher than 3 for all hotels, which reveals the presence of very fat tails (i.e., a common use of extreme last-minute price adjustments). Analogously, the skewness is always greater than zero, which indicates the predominance of last-minute surcharges over last-minute discounts.

The chain hotels (*H*1 and *H*6) show pricing policies that seem more attentive to the customers' perceptions. For these hotels, the kurtosis is smaller than the others. By contrast, the small values of skewness indicate a better balance in forecasting peaks in last-minute reservations and cancellations. The 3-star hotels (most of all, *H*4) seem more prone to relying on price tactics, i.e., at the last minute they post price $P_{t,0}$ on the Internet that may be very different from what they expected at time $t-14$. Tactics are mostly last-minute discounts on the price they post in $t-14$ for a stay in t. However, the fact that the skewness is always positive and greater than one

Table 3 Empirical skewness and excess kurtosis of the price shocks $\epsilon_{t,14}$

	Skewness	Excess kurtosis
*H*1	0.61	4.29
*H*2	1.63	8.79
*H*3	1.07	6.54
*H*4	2.95	22.34
*H*5	0.11	6.87
*H*6	0.92	3.40

suggests that, on some days, they manage to offer very high prices (i.e., the average of the last minute discount is higher than its median). The comparisons between the *AIC* and *BIC* criteria for *Model 1* and *Model 2* (see Table 4) indicate that, for all six hotels, the highest goodness-of-fit is obtained when the error term $\epsilon_{t,14}$ is modeled using a skew-*t* distribution. Thus, the non-normal model yields a better description of the behavior of all the observed decision-makers. This empirical evidence, albeit stemming from a small sample of hotels, would suggest that the choice of the distribution of $\epsilon_{t,14}$ plays a fundamental role in evaluating the price differentiation techniques applied by the hoteliers.

Finally, let us focus on the two hotels with the extreme pricing behavior in terms of kurtosis. They are also the hotels with the lowest and highest number of rooms and services offered. For Hotels $H4$ and $H6$, the empirical density of the price shocks (see Figs. 1 and 2) show a large number of extreme values and is largely asymmetric with a longer right tail. We also note that *Model 1* is not capable of fully reproducing the data, even though the observed skewness and kurtosis are closer to those of the Gaussian distribution. Figures 3 and 4 show the time series of the price shocks for Hotels $H4$ and $H6$. The two plots highlight the asymmetry of ϵ_t, which is reflected by the more elongated right tail. Thus, we still arrive at the same conclusion: a skew-*t* distribution allows for a more realistic representation of the unobserved price shocks.

4.2 The static approach: estimation

We might expect the price $P_{t,14}$ to be endogenously correlated with ϵ_t. For example, if the "old good RM rule" to sell the best rooms first (Escoffier 1997) is followed, second-order price discrimination tactics could be considered an omitted variable affecting both $P_{t,14}$ and $P_{t,0}$. Endogeneity issues could occur because the last minute adjustment $\epsilon_{t,14}$ might incorporate information about the hotels' early booking occupancy, thus affecting $P_{t,14}$. To handle possible endogeneity problems, we use an instrumental variable approach. Specifically, for each hotel, we choose the average of the prices $P_{t,14}$ of the other five hotels as the instrument. This average is not expected to be correlated with the error ϵ_t, since the six selected hotels have different locations, star ratings, sizes, features and—most of all—they do not have interlocking directorates, as we checked using the

Table 4 *AIC* and *BIC* criteria

	Model 1		*Model 2*	
	AIC	*BIC*	*AIC*	*BIC*
$H1$	6637.28	6650.66	6476.19	6498.50
$H2$	6443.24	6456.63	5984.28	6006.58
$H3$	6630.25	6643.63	6279.16	6301.46
$H4$	6990.06	7003.44	6479.66	6501.97
$H5$	5606.61	5619.99	5340.10	5362.41
$H6$	6853.82	6867.20	6574.55	6596.86

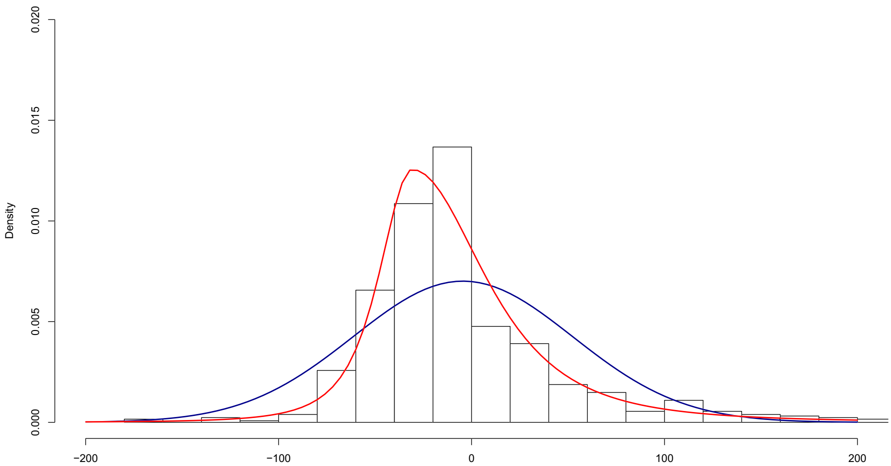

Fig. 1 Empirical distribution of price shocks for Hotel *H*4. *Model 1* (blue) and *Model 2* (red) (colour figure online)

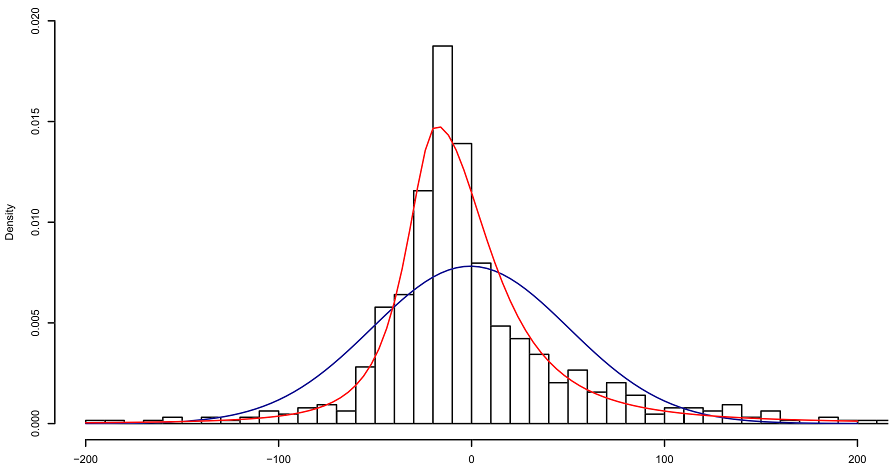

Fig. 2 Empirical distribution of price shocks for Hotel *H*6. *Model 1* (blue) and *Model 2* (red) (colour figure online)

Bureau-Van-Dijk's AIDA database. Further, we test the relevance of the instrument and we find that it is strongly correlated with $P_{t,14}$ for every hotel. When we regress $P_{t,14}$ on the instrument, the F-statistic varies from 1154 for Hotel $H3$ to 3410 for Hotel $H6$. Then, by running the Durbin-Wu-Hausman test, we find that $P_{t,14}$ is endogenous for each of the six hotels (p-value < 5%). Therefore, we estimate the parameters of *Model 1* and *Model 2* by using the 2–stage procedure introduced in Sect. 3.3. We report the results in Table 5. As we see, both the specifications indicate the evidence of price discrimination practices. The parameter b_{14} is always significant and positive, revealing that the RM systems

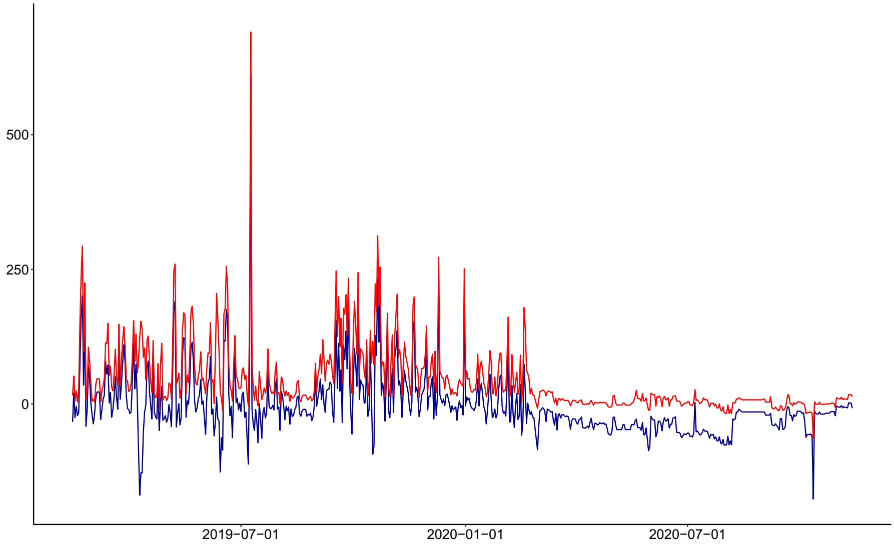

Fig. 3 Price shocks of Hotel *H*4. *Model 1* (blue) and *Model 2* (red) (colour figure online)

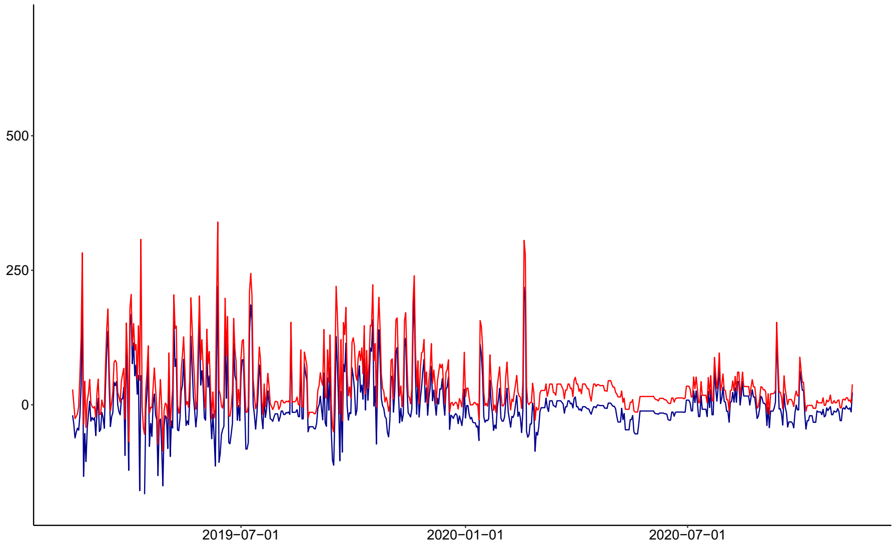

Fig. 4 Price shocks of Hotel *H*6. *Model 1* (blue) and *Model 2* (red) (colour figure online)

fix prices at $t - k$ in line with the last-minute price (i.e., hoteliers can accurately predict stochastic seasonality). Moreover, μ_{14} is positive and significant, thus we find evidence of price discrimination practices that do not vary with the calendar time t. The parameter b_{14} is always smaller than one, reaching the lowest values for Hotels $H3$, $H4$ and $H6$. The first two of these accommodation structures are 3-star hotels whose average prices in t tend to be lower than those proposed at

Table 5 Estimated parameters of *Model 1* and *Model 2*

Model 1	μ_{14}	*SE*	b_{14}	*SE*
$H1$	21.030	4.512	0.880	0.032
$H2$	15.730	3.508	0.917	0.043
$H3$	29.170	3.870	0.732	0.045
$H4$	24.040	5.294	0.827	0.052
$H5$	11.950	2.261	0.920	0.046
$H6$	62.470	4.651	0.799	0.033
Model 2	μ_{14}	*SE*	b_{14}	*SE*
$H1$	6.710	5.523	0.919	0.043
$H2$	2.580	1.099	0.690	0.016
$H3$	25.680	1.556	0.533	0.015
$H4$	36.060	2.212	0.343	0.025
$H5$	16.950	5.883	0.680	0.148
$H6$	69.660	2.220	0.544	0.012

$t-14$ (see Table 2). Their strategy appears simple: they set relatively high prices at $t-14$ to keep inventory for the last minute. They are more worried about missing the opportunity to further increase prices at the last-minute than about having to offer large discounts in t to increase the occupancy rate. The case of $H6$ is the opposite, as the large value of μ_{14} suggests that, despite the prices set in $t-14$, the hotel can raise the last minute rates for every t. It's important to note that $H6$ is a 4-star chain hotel, which is very attractive to business travelers, the segment less elastic to price.

The fit of *Model 1* is always worse than *Model 2*, so we can assume that the coefficients estimated under the skew-t assumption better reflect the price discrimination policy of every hotel. The value of b_{14} is smaller under skew-t errors, showing that the effect of the early booking prices on the last-minute rates is biased if the last minute response to demand shocks is constrained to be symmetric and without fat tails. The only exception is for Hotel $H1$, for which μ_{14} is not significant and b_{14} is close to (and less than) one, reflecting a wide uniformity of prices between early and late booking (see Table 2). We can speculate that such an approach to pricing responds to a chain logic, e.g., communicating stable prices to the on-line potential customers or keeping a buffer of rooms available at the last minute to re-protect overbooking of other affiliated structures. However, the asymmetric errors and thick tails lead us to conclude that both models fail to predict extreme scenarios, especially the most negative ones (i.e., more cancellations or fewer reservations than expected). This conclusion is consistent with the findings of Mitra (2020).

4.3 Time-varying parameters: a framework to assess RM practices

Let us consider *Model 3*, according to which the conditional location, volatility, kurtosis, and skewness of $\epsilon_{t,k}$ are assumed to be time-varying. This way, the dependence of the error on the seasonality becomes a further dimension that we can use to evaluate dynamic pricing practices. To model the time dependence of the above four characteristics, we use an autoregressive process of order one (see relation (8) in the "Appendix"). We estimate the parameters for each of the six hotels using the 2−stage procedure introduced in Sect. 3.3. We report results in Table 6. We first stress that introducing time-varying parameters in the shock term improves the goodness-of-fit. The *AIC* and *BIC* statistics are much smaller for *Model 3* than for the two models with constant parameters (compare Table 6 with Table 5). The improvement is for all six hotels. If we consider a stochastic dynamic for the parameters of the error $\epsilon_{t,14}$, the coefficient b_{14} declines, and the weight of last-minute adjustments due to unpredicted demand and/or pricing tactics increases. In other words, allowing for a dynamic location to manage/react to stochastic seasonality reduces the weight given to $P_{t,14}$ in favor of that given to the last minute (stochastic) discount/surcharge. Hotels $H4$ and $H6$ represent the two extremes. The former has a very simple RM system with a b_{14} parameter almost equal to zero and a $\phi_{\mu_{14}}$ coefficient close to one (0.981). The early booking price is therefore set with little knowledge of the events that can cause excess demand (i.e., $P_{t,14}$ does not replicate $P_{t,0}$). The hotel is applying a simple additive price discrimination policy that tends to persist over time (the discounts for the advance booking simply follow a long-term—i.e., weekly or monthly—seasonality). On the contrary, $H6$ has a more advanced pricing system, with last-minute prices proportional to the early booking ones and with discounts/surcharges for the advance booking that vary on a daily basis. That is, they are almost serially uncorrelated at lag 1 (the $\phi_{\mu_{14}}$ coefficient is equal to 0.1).

We argue that further investigation of the persistence of the higher moments of the distribution of $\epsilon_{t,14}$ may lead to a more in-depth inference on the "mechanics" of each RM system. Therefore, we are going to assess the ability of the revenue management policies to learn from the past, based on the autoregressive coefficients $\phi_{\lambda_{14}}$, $\phi_{\psi_{14}}$ and $\phi_{\xi_{14}}$. The scale of the error term informs us about the dispersion around its location. The estimated parameters $\phi_{\lambda_{14}}$ are relatively high, indicating that the last-minute adjustments are uniform across different seasons t. The only exception is Hotel $H2$, which occasionally presents peaks in the scale due to very high last-minute discounts in the low seasons. The large and negative difference between the q_{10} for t and $t-14$ (see Table 2) also reflects this. On the opposite side, we find the chain Hotel $H6$, for which $\phi_{\lambda_{14}}$ is almost equal to one. This finding indicates that the RM system pays attention to price fairness and/or that the pricing dynamic is based more on a long-memory strategy rather than occasional last-minute tactics. The kurtosis of $\epsilon_{t,14}$ measures the propensity of each hotel to make "extreme" forecasting errors for different arrival days. As for its autocorrelation parameter $\phi_{\psi_{14}}$, we note that it is never smaller than 0.55, a value highlighting that the accuracy in predicting demand peaks remains quite constant over time. Unfortunately, the parameters do not inform us regarding the revenue managers' forecasting ability (i.e., the magnitude of the "extreme" forecasting errors). Thus, we can only conclude that is difficult for these hotels to use previous experience to reduce the probability of making extreme relative price adjustments. The autocorrelation in the kurtosis parameters also shows a very low variability among the hotels, reaching its minimum for $H2$ and $H5$, the only medium-sized hotels without a restaurant. These two

Table 6 *Model 3*, estimated parameters and information criteria

Model 3	b_{14}	*SE*	$\phi_{\mu_{14}}$	*SE*	$\phi_{\lambda_{14}}$	*SE*	$\phi_{\psi_{14}}$	*SE*	$\phi_{\xi_{14}}$	*SE*	*AIC*	*BIC*
*H*1	0.359	0.006	0.723	0.002	0.807	0.001	0.912	0.002	0.936	0.002	6212.53	6270.53
*H*2	0.356	0.006	0.496	0.000	0.245	0.000	0.557	0.001	0.929	0.000	5633.83	5691.83
*H*3	0.399	0.005	0.422	0.000	0.724	0.000	0.869	0.000	−0.218	0.000	5953.91	6011.91
*H*4	0.010	0.003	0.981	0.000	0.972	0.000	0.924	0.001	0.817	0.001	5731.41	5789.41
*H*5	0.288	0.000	0.463	0.000	0.710	0.000	0.621	0.000	0.582	0.000	4898.90	4956.90
*H*6	0.358	0.000	0.100	0.000	0.996	0.000	0.945	0.000	0.915	0.001	6323.01	6381.01

accommodation structures are also the ones with the lowest average rates, thus we can argue that they are the more attractive to the leisure segment. Therefore, they would find it difficult to sell rooms to walk-in guests at “any” price, e.g., to last-minute business customers who have not found available rooms during important events and fairs held in Milan. Finally, the relatively high average value (0.66) of the autocorrelation of the asymmetry parameter $\phi_{\xi_{14}}$ suggests that last-minute surcharges and discounts maintain the same sign for several consecutive arrival days t. Such a persistence reflects a possible bias in forecasting last-minute reservations/cancellations or even a strategy aimed at saving an optimal stock of rooms for last-minute sales (setting $P_{t,14}$ accordingly). However, the high variability of the $\phi_{\xi_{14}}$ parameters across the observed hotels points to the existence of very different forecasting abilities and/or last-minute pricing tactics. In particular, the autocorrelation parameter for Hotel $H3$ is negative, meaning that its pricing system alternates higher and lower than the average last-minute price adjustments, “self-correcting” the asymmetry of the last minute price shocks.

4.4 Main empirical findings

For all the six hotels considered, the introduction of time-varying parameters in the shock term yields the highest goodness-of-fit. In this case, we observe a weaker influence of early booking prices on revenue management compared to the last-minute (stochastic) discount/surcharge. The tendency to rely on last-minute tactics for dynamic pricing seems to be influenced more by the size of the hotel rather than its star rating. Specifically, we observed that larger-sized, 3-star hotels exhibit more dynamic adjustments in last-minute pricing over time t. Chain hotels, in particular, pay close attention to consumers’ perception of price fairness over time, maintaining a significant level of price consistency between early and late bookings. It is uncommon to find significant discounts or surcharges during the last-minute period. However, larger chain hotels are more inclined towards dynamic pricing, especially by setting significantly higher prices during trade fair periods. The 3-star hotels are more prone to apply last-minute discounts on the price they post in $t-14$ for a stay in t, albeit sometimes they rely on a higher last-minute price to speculate on (unforseen) demand peaks. Our approach has allowed us to demonstrate that the autocorrelation values of the four studied moments reveal essential characteristics of pricing strategies. Notably, this is the first time in the literature that an objective and transparent method (i.e., based on publicly available data) has been proposed to utilize skewness and kurtosis dynamics in analyzing decision-makers’ propensity towards extreme last-minute adjustments (kurtosis) and last-minute discounts or surcharges (skewness). To further highlight the usefulness and applicability of the proposed approach, we focus on the two hotels with extreme pricing behavior ($H4$ and $H6$) and delve into the dynamics of the error distribution parameters. In Fig. 5 we show the dynamics of the location parameter for Hotel $H4$. As we may see, the advance booking premium ($\mu_{t,14}$) is quite persistent, i.e., it is planned according to a low-frequency pattern. This implies that the

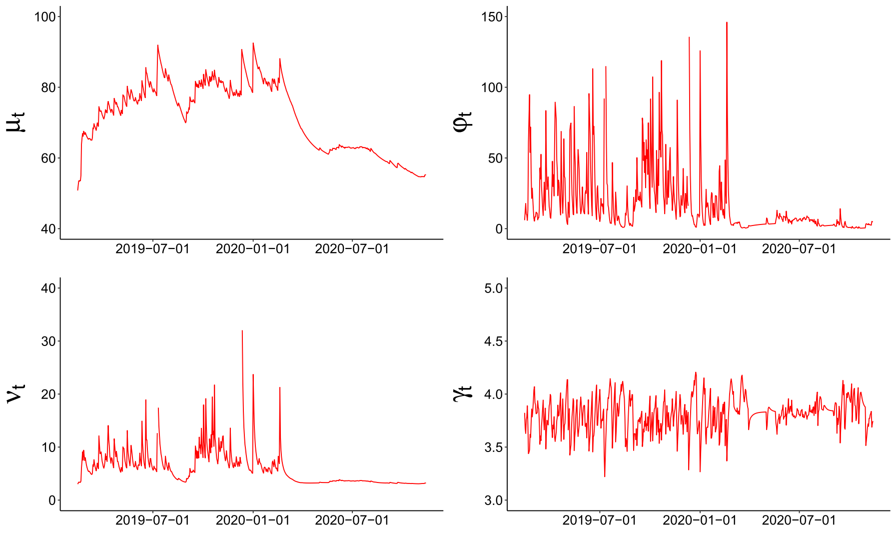

Fig. 5 Filtered parameters for *Model 3* and Hotel *H*4. From the top left, clockwise: location, scale, asymmetry, degrees of freedom

last-minute reservations do not follow short-term seasonality (i.e., a weekend or a week-day seasonality), or even that the RM system cannot predict (and manage via dynamic pricing) high-frequency shocks in the last-minute demand. The large values of the scale parameter (compared to the location) confirm that the price $P_{t,14}$ is not used as a lever for inter-temporal price discrimination, i.e., $P_{t,14}$ is set without considering (or accurately predicting) the stochastic seasonality. The quite persistent dynamics of last minute adjustment translates into an almost constant pattern after March 2020 (i.e., after the collapse of tourism demand due to Covid-19). The effect of the pandemic is particularly interesting if we look at the kurtosis. The probability of observing an extreme price adjustment has increased (the degrees of freedom $\nu_{t,14}$ has decreased), becoming almost flat over time. The hotel has lost any residual ability to predict changes in the demand (or it stopped practicing dynamic pricing at advance booking $k = 14$) even during the summer and the early autumn of 2020, when mobility restrictions were relaxed and tourism demand recovered. By contrast, Hotel *H*6 (see Fig. 6) in the Covid-19 period did not change the way it managed pricing, with the only exception that it reduced rates and—consequently—the adjustments for advance booking ($\mu_{t,14}$). This hotel has a very reactive RM system, as highlighted by the peaks in both the degrees of freedom and the skewness observed between the first and the second wave of Covid-19 when some important fairs and events took place. The constant reduction in the scale (see the $\varphi_{t,14}$ curve) is also a positive feature, mostly because it happens regardless of the probability of observing extreme last-minute corrections (see $\nu_{t,14}$). This suggests that even under the mobility restrictions due to Covid-19, the RM system is still capable of setting

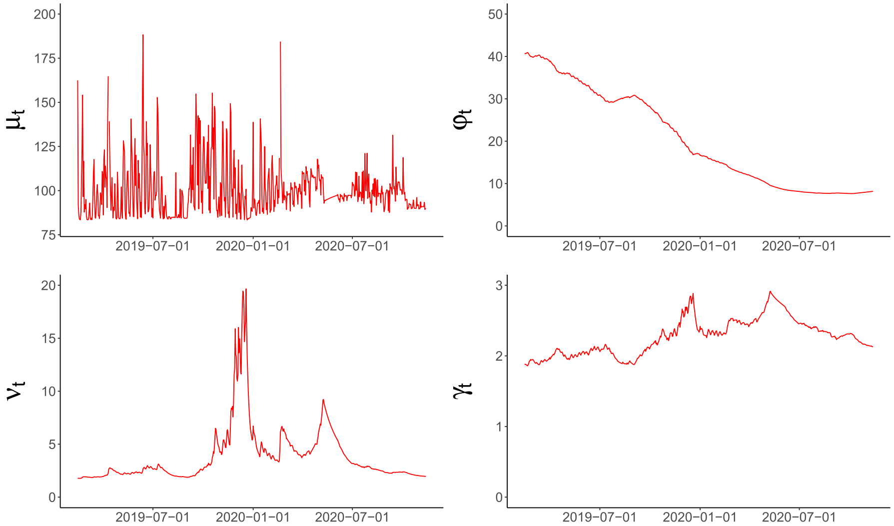

Fig. 6 Filtered parameters for *Model 3* and Hotel *H*6. From the top left, clockwise: location, scale, asymmetry, degrees of freedom

values for $P_{t,14}$ "in line" with $P_{t,0}$. It is worth mentioning that a scale reduction is a powerful tool to manage the customers' perception of price fairness. Indeed, according to Choi and Mattila (2018), the offered prices influence the reference price, which is beneficial for to travelers' perception of price acceptability and re-booking propensity.

5 Conclusions

We propose a nonlinear statistical framework for "reverse-engineering" intertemporal price discrimination practices in the presence of a stochastic seasonality. This is new to the dynamic pricing literature as a way to assess a revenue management system based on information that is publicly available on the internet and a statistical (transparent) method. The idea is to observe the gap between rates posted on-line at different advance bookings for the same product and arrival date. We consider such a price adjustment stochastic, as it originates in the departure of the realized demand (i.e., the unpredictable fluctuations of the daily demand) from the pick-up rates planned/forecasted by revenue managers based on the current inventory. The econometric specification we propose is straightforward: a linear model where the "expected" price at day t is a function of the price posted by the decision-maker at $t-k$ (i.e., at the advance booking k) plus a stochastic shock/adjustment. We consider the early booking rate, the most complete publicly available information regarding the expectation of decision-makers about the "right" pricing at the last-minute, conditioned on the knowledge they have at $t-k$. Thus, the last-minute price adjustment reflects the consequences of a pure forecasting error about the demand on the arrival day and/or a bias due to last-minute tactics based on inventory management. In the dynamic pricing literature, the size of the last-minute shocks has been thoroughly investigated, but their variability and asymmetry (discounts/surcharges) have largely been overlooked. Moreover, we are the first to analyze the fourth moment of the probability distribution of last-minute adjustments, the kurtosis, interpreting it as the likelihood to observe extreme peaks (either positive or negative) in the last-minute demand. We model the above four moments dynamically based on a score-driven approach, which we take from finance and bring into management. Specifically, we propose it as a tool to reverse-engineer the time-heterogeneity of the last-minute adjustment practiced by any hotel that regularly publishes rates online. We point out that a hotel can use our methodology either to learn about possible limitations (or strengths) of its RM system or to analyze the behavior of competitors based only on publicly available information. Our approach does not require any specific knowledge of the events taking place near the hotel or the features of the hotel. The prices offered in the early booking period, together with the price adjustments, already reflect the hoteliers' knowledge and expectations regarding both stochastic peaks in the demand and possible spillovers on adjacent arrival days. An empirical application is presented where we consider six hotels in Milan, a city where the daily demand has strong (unpredictable) fluctuations due to weekends and recurrent fairs and events. These hotels, which are equally divided between 3-star and 4-star and managed by non-interlocking directorates, posted prices regularly during the time interval from February 13, 2019 to November 11, 2020. We first highlight that last-minute price adjustments, i.e., the hoteliers' reaction to demand shocks, are correctly described by a heavy-tailed distribution such as the skew-t rather than a Gaussian model. In other words, asymmetric errors and thick tails indicate an unequal proportion between discounts and surcharges and a higher probability of extreme values compared to the Gaussian case. This finding leads us to conclude that, more than anything, all the RM systems we considered fail to predict extreme negative scenarios (i.e., more cancellations or fewer reservations than expected). A second (expected) result is that allowing for a stochastic dynamic in the parameters of the last-minute adjustment yields a better representation of the observed pricing behavior. However, our small sample shows large differences in the way the six accommodation structures use last-minute discount/surcharge tactics to address possible forecasting errors of the pick-up curve. The lowest-rated hotels tend to set relatively high prices at the early booking to keep the inventory free for the last-minute, aiming at applying high surcharges. The highest-rated hotels seem less prone to relying on last-minute tactics. They tend to apply (only) last-minute overpricing or keep uniform prices between early and advance booking. Moreover, the pricing policies of the chain hotels seem more attentive to the customers' perceptions (as documented by the constancy of the scale parameter) and more accurate (and balanced) in forecasting positive and negative peaks in last-minute reservations and cancellations. All of the six hotels considered apply time-varying discrimination policies that are more frequently additive than proportional to early booking prices. However, the way they deal with last-minute stochastic seasonality is not homogeneous. In particular, their RM systems show differing abilities in "pricing" the stochastic demand. Looking at the autocorrelation in the location parameters, the most evident fact is the great differences between the 3-star hotel with the lowest number of rooms, $H4$, and the 4-star hotel with the highest number of rooms and meeting rooms, $H6$. Hotel $H4$ applies a simple additive price discrimination policy that tends to persist over time (the price adjustment for the advance booking simply follows a long-term—i.e., weekly or monthly—seasonality). In contrast, hotel $H6$ has a pricing system able to handle daily seasonality, with the last minute price adjustments that are almost serially uncorrelated at lag 1 (i.e., they vary with daily frequency). More in general and in line with Reino et al. (2016), the substantial absence of a revenue strategy seems driven by the hotel size rather than the star rating, at least in our small sample. In fact, we note that other, larger-sized, 3-star hotels show more dynamic last-minute price adjustments over time t. If we focus on the autocorrelations of the variability of the price shocks (the scale parameter), they are relatively high. This finding indicates that the uncertainty regarding last-minute rates remains smooth across different seasons t for five out of the six hotels. The hotel with the shortest memory in the scale parameter is a 3-star accommodation structure that occasionally offers very high last-minute discounts in periods with no large events or during the weekends. For this hotel, the average value of the scale parameter is high, which confirms that the RM system sets early booking prices without considering (or accurately predicting) the stochastic seasonality. Chain hotels show both the highest persistence in the rates' variance across seasons and a low average value of the scale parameter. Thus, we can conclude that they are attentive to potential consumer perceptions of price fairness issues For all six hotels, the kurtosis of the price shocks shows very high autoregressive coefficients. Thus, their RM systems tend to maintain the same accuracy (either high or low) in forecasting jumps in last-minute occupancy rates over the considered time interval. This finding is presumably due to the fact that the attractiveness of a single fair or event is hard to quantify by single hotels with $k = 14$ days of advance booking. It does not seem to be a coincidence that the accommodation structures with the less persistent dynamics in the kurtosis parameter are also the least exposed to the business segment. These low-rated and less-equipped hotels with common spaces become attractive for the richest business segment only in a few periods during very high season, when the excess demand allows them to occasionally apply high last-minute price surcharges. Finally, looking at the dynamics of the symmetry parameter, we note that all the RM systems tend to maintain the same propensity to over/underestimate the demand level at the last-minute across seasons. In other words, the forecasting algorithms of the last- minute occupancy rates are biased, as hotels tend to systematically propose last-minute discounts (or surcharges) which are not proportional to early booking prices. The only exception is with our only 3-star hotel with a restaurant, which seems to follow an inconsistent pricing policy between consecutive days since it (alternatively) offers last-minute price adjustments that are higher and lower than the average. To further investigate such behavior, it would be interesting to interview the revenue manager at the hotel (if there is one). However, we point out that our methodology allows us to detect this type of "non-smooth" pricing strategy.

Appendix

To calculate the unrestricted score in (8), we need to consider the conditional log -density of $\epsilon_{t,k}$, which we parametrize as in Harvey and Sucarrat (2014):

$$\begin{aligned}\ln p(\epsilon_{t,k}|\mathcal{F}^k_{t-1},\boldsymbol{\vartheta}_k) = & \ln 2 - \ln(\gamma_{t,k} + 1/\gamma_{t,k}) + \ln\Gamma\left(\frac{\nu_{t,k}+1}{2}\right) - \ln\Gamma\left(\frac{\nu_{t,k}}{2}\right)\\ & - \frac{1}{2}\ln\pi - \frac{1}{2}\ln\varphi^2_{t,k}\\ & - \frac{\nu_{t,k}+1}{2}\ln\left(1 + \frac{(\epsilon_{t,k}-\mu_{t,k})^2}{\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}\nu_{t,k}\varphi^2_{t,k}}\right).\end{aligned} \tag{10}$$

The driving-force $\boldsymbol{s}_{t,k}$ is computed as follows

$$\boldsymbol{s}_{t,k} = \boldsymbol{J}^{\top}_{t,k}\boldsymbol{\nabla}_{t,k}, \tag{11}$$

where $\boldsymbol{\nabla}_{t,k} = \frac{\partial \ln p(\epsilon_{t,k}|\mathcal{F}^k_{t-1},\boldsymbol{\vartheta}_k)}{\partial \boldsymbol{f}_{t,k}}$ is the score vector of the predictive log-density in (10), and $\boldsymbol{J}_{t,k} = \frac{\partial\boldsymbol{\Lambda}(\boldsymbol{f}_{t,k})}{\partial\boldsymbol{f}^{\top}_{t,k}}$ is the Jacobian matrix of the nonlinear mapping $\boldsymbol{\Lambda}(\cdot)$. By taking derivatives in (7), we have

$$
\boldsymbol{J}_{t,k} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \exp\{\lambda_{t,k}\} & 0 & 0 \\ 0 & 0 & \exp\{\psi_{t,k}\} & 0 \\ 0 & 0 & 0 & \exp\{\xi_{t,k}\} \end{bmatrix},
$$

whereas $\boldsymbol{\nabla}_{t,k} = (\nabla^{\mu}_{t,k}, \nabla^{\varphi}_{t,k}, \nabla^{\nu}_{t,k}, \nabla^{\gamma}_{t,k})^{\top}$ in Eq. (11) is computed as follows

$$
\begin{aligned}
\nabla^{\mu}_{t,k} &= \frac{\partial \ln p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k)}{\partial \mu_{t,k}} \\
&= \begin{cases} \frac{(\nu_{t,k}+1)(\epsilon_{t,k}-\mu_{t,k})/(\gamma_{t,k}^{-2}\nu_{t,k}\varphi_{t,k}^2)}{1+(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{-2}\nu_{t,k}\varphi_{t,k}^2)} & \text{if } (\epsilon_{t,k}-\mu_{t,k}) \in (-\infty, 0), \\ \frac{(\nu_{t,k}+1)(\epsilon_{t,k}-\mu_{t,k})/(\gamma_{t,k}^{2}\nu_{t,k}\varphi_{t,k}^2)}{1+(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2}\nu_{t,k}\varphi_{t,k}^2)} & \text{if } (\epsilon_{t,k}-\mu_{t,k}) \in [0, +\infty), \end{cases} \\
\nabla^{\varphi}_{t,k} &= \frac{\partial \ln p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k)}{\partial \varphi_{t,k}} \\
&= \begin{cases} \frac{1}{\varphi_{t,k}}\left(\frac{(\nu_{t,k}+1)(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{-2}\nu_{t,k}\varphi_{t,k}^2)}{1+(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{-2}\nu_{t,k}\varphi_{t,k}^2)} - 1\right) & \text{if } (\epsilon_{t,k}-\mu_{t,k}) \in (-\infty, 0), \\ \frac{1}{\varphi_{t,k}}\left(\frac{(\nu_{t,k}+1)(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2}\nu_{t,k}\varphi_{t,k}^2)}{1+(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2}\nu_{t,k}\varphi_{t,k}^2)} - 1\right) & \text{if } (\epsilon_{t,k}-\mu_{t,k}) \in [0, +\infty), \end{cases} \\
\nabla^{\nu}_{t,k} &= \frac{\partial \ln p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k)}{\partial \nu_{t,k}} = \frac{1}{2}\left[\Psi\left(\frac{\nu_{t,k}+1}{2}\right) - \Psi\left(\frac{\nu_{t,k}}{2}\right) - \frac{1}{\nu_{t,k}}\right. \\
&\quad - \ln\left(1 + \frac{(\epsilon_{t,k}-\mu_{t,k})^2}{\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}\nu_{t,k}\varphi_{t,k}^2}\right) \\
&\quad \left. + \frac{\nu_{t,k}+1}{\nu_{t,k}}\left(\frac{(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}\nu_{t,k}\varphi_{t,k}^2)}{1+(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}\nu_{t,k}\varphi_{t,k}^2)}\right)\right], \\
\nabla^{\gamma}_{t,k} &= \frac{\partial \ln p(\epsilon_{t,k}|\mathcal{F}^k_{t-1}, \boldsymbol{\vartheta}_k)}{\partial \gamma_{t,k}} = \frac{1-\gamma_{t,k}^2}{\gamma_{t,k}^3+\gamma_{t,k}} + \mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})-1} \\
&\quad \times \frac{\nu_{t,k}+1}{\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}}\left(\frac{(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}\nu_{t,k}\varphi_{t,k}^2)}{1+(\epsilon_{t,k}-\mu_{t,k})^2/(\gamma_{t,k}^{2\mathrm{sgn}(\epsilon_{t,k}-\mu_{t,k})}\nu_{t,k}\varphi_{t,k}^2)}\right),
\end{aligned}
$$

where $\Psi(x) = \frac{d}{dx}\ln\Gamma(x)$ is the so-called digamma function, see Abramowitz and Stegun (1964).

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Declarations

Conflict of interest The authors have no conflicts of interests or Conflict of interest to declare.

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