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A temporal construal theory explanation of the price-quality relationship in online dynamic pricing

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ABSTRACT

According to construal theory, the desirability of a product influences consumers' choices from a temporally, socially, spatially and hypothetically distant perspective. The purpose of this study is to test the temporal dimension of such theory with reference to hotel room prices, also distinguishing by firm size. Temporal distance is measured through the days of advance booking, in a varying-coefficient model reflecting both the dynamic pricing behaviour of the supply and the seasonal oscillation pattern of the demand. Results support the appropriateness of the temporal construal theory as an interpretative framework for the effectiveness of dynamic pricing, from the perspective of behavioural psychology. On average, the influence of quality on price in small hotels is lower than in large hotels; however, its variability is higher in small hotels. Large hotels charge a premium price during peak season dates, while small firms apply discounts, likely aiming to reach full occupation.

1. Introduction

Adopting an effective pricing strategy is crucial for business success, especially in economic downturns as that consequent to the COVID-19 pandemic, for the firm to maintain sales volume and appropriate the highest possible market value (Piercy et al., 2010; Hutchins, 2020). The literature about pricing is extensively developed, however pricing practices are continuously evolving and this topic still holds considerable interest for both scholars and practitioners (Phillips, 2021). In particular, dynamic pricing, pioneered since the mid-Eighties by airlines and large hotel chains, is spreading also among small businesses, especially in the travel and tourism sector, where it constitutes a viable solution to adjust the offer to market movements, given their stiff cost structure (Alderighi, Nicolini, & Piga, 2015; Melis & Piga, 2017; Xie & Kwok, 2017; Oskam, van der Rest, & Telkamp, 2018; Abrate, Nicolau, & Viglia, 2019). In fact, it has been shown that proper short-term price changes, based on advance booking, can allow firms to obtain important price premiums, affecting the economic performance positively and increasing competitiveness (Sweeting, 2012; Sen et al., 2013; Abrate & Viglia, 2016; Abrate et al., 2019; Guizzardi et al., 2019).

Almost all extant empirical studies about dynamic pricing assume the relationship between advance booking and price to be deterministic (e.g. Abrate & Viglia, 2016; Jang, Chen, & Miao, 2019; Soler, Gemar, Correia, & Serra, 2019). However, hotel managers modulate their market power lever and preferences-based segmentation practices across advance bookings, thus, ignoring these factors in rooms rates modeling could lead to an omitted variable bias on the estimated shadow prices (Cotteleer, Gardebroek, & Luijt, 2008; Lee, 2018). Despite these warnings, very few studies explicitly consider that the relationship between price and customers' preferences could change along the booking window, since any product feature/attribute may become more (less) important for the consumer's choice, as the time of purchase approaches that of consumption. To the best of our knowledge, only Abrate et al. (2019) and Guizzardi, Angelini, and Pons (2020) have proposed a dynamic pricing approach in this specific sense. The former employ price changes count and coefficients of price variation as explanatory variables for hotel revenue; the second specify the stochastic dynamic of room rates across advance booking periods directly. However, to the best of our knowledge, so far, no study has tried to add the time-varying quality score in the analysis and to frame such a stochastic relationship within a consumer psychology theory. Thus, the goal of this work consists in testing the adequacy of the construal level theory to explain the

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effectiveness of dynamic pricing from the perspective of behavioural psychology.

Born as a framework for investigating the psychological mechanisms of mental representation in goal-oriented decision-making processes, the construal level theory has been recently applied in more interdisciplinary research, especially in consumer studies (Adler & Sarstedt, 2021; Ding, Zhong, Guo, & Chen, 2021). There, 'high-level construal' refers to the consideration of the characteristics making a product desirable, while 'low-level construal' indicates evaluations of the feasibility of the purchasing (Cho, Khan, & Dhar, 2013; Ding & Keh, 2017). The desirability of a product depends on the core benefits the customer expects from it and, according to the construal level theory, it is more salient when the decision-maker is psychologically distant from consumption, while feasibility relates to the cost of purchasing and using a good, which should matter more the psychologically closer the consumption (Trope, Liberman, & Wakslak, 2007). The empirical literature has confirmed the validity of this theory in many consumption contexts (e.g. Castaño, Mita, Manish, & Harish, 2008; Kim, Park, & Wyer, 2009; Gao, Wang, & Bailey, 2021). However, recently warnings have been issued against an excessive generalization of the relations found for certain dimensions of psychological distance, on limited samples (Sanchez, Coleman, & Ledgerwood, 2021; Adler & Sarstedt, 2021). In fact, psychological distance is articulated in four interrelated dimensions: temporal distance, spatial distance, social distance, and hypotheticality, each with its unique characteristics, operating specifically in different contexts, that deserve dedicated deep investigations (Adler & Sarstedt, 2021). Consistently, this study focuses on temporal distance, which is of particular interest for marketing studies, as it has been shown to bear an important influence on daily buying decisions of consumers (Cho et al., 2013; Ding & Keh, 2017). Moreover, in dynamic pricing, the advance booking time looks especially appropriate to be interpreted in terms of temporal distance.

Thus, in order to test whether the construal level theory, limited to its temporal dimension, can provide an adequate interpretative framework for dynamic pricing from the perspective of behavioural psychology, we measure hotel's desirability by means of user-generated overall quality score, published on Booking.com, and assume that price (retrieved from the same source) can reveal the customer's assessment of the feasibility of the purchase. Then, we estimate the stochastic relationship linking prices and desirability of the lodging service, on the room rates of 102 hotels in Venice, recorded at 17 different lengths of advance booking for each date between April the 1st, 2019 and February the 29th, 2020. A varying-coefficient additive approach is proposed to estimate time-varying "elasticities" of price to quality score. This way, the dynamic relationship between quality and price at various advance bookings, and the seasonal pattern (namely, the dynamics of prices over calendar time) are considered simultaneously. This latter aspect has been shown to be especially relevant, in view of the revenue maximization strategies adopted by hotels (Abrate et al., 2019; Guizzardi et al., 2020). However, before carrying out such statistical analysis of online prices, we test whether the relationship between quality and price can be interpreted in terms of causality, through an online experiment, asking hotel managers how much they would change the price they set for a given room at a certain check-in date, in case the online quality score were one level higher or lower, ceteris paribus.

To the best of our knowledge, this is the first work that tests the temporal construal theory in a doubly dynamic model (considering both the stochastic and deterministic dynamics of room rates, along with the dynamic relationship with quality). Moreover, we apply the proposed methodology to small and large hotel firms separately, testing if the temporal construal theory holds regardless of firm size.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and develops the focal hypotheses. Section 3 illustrates the experiment aimed at testing causality. In section 4 we present the statistical analysis of hotel prices, testing if the temporal construal theory holds. In the last and concluding section, we discuss the key findings, illustrate the research contributions and managerial implications, identify the research limitations and directions for future research.

2. Literature review and research hypotheses

2.1. The construal level theory

The construal level theory is a behavioural psychology model of the different degrees of abstraction involved in the representation of events (Gao et al., 2021). The theory distinguishes between two levels. At the high construal level there are abstract and essential representational traits, related to the subject's evaluation of behavioural goals and values (Liberman & Trope, 2008; Liberman, Trope, & Wakslak, 2007). At the low construal level, we find concrete and more superficial characterizations of the event, linked to goals attainability, including means and efforts required (Fujita, Eyal, Chaiken, Trope, & Liberman, 2008; Trope & Liberman, 2010). The salience of representational features located at either construal level depends on the psychological distance of the decision-maker from the action he/she assesses (Liberman et al., 2007). In fact, close events can be directly experienced, allowing the decision-maker to get detailed, contextualized and extensive information about them. Conversely, the subject is able to retrieve much less information about far events, that he/she cannot access directly, thus, he/she must decide based on an abstract mental representation of the action's consequences (Liberman & Förster, 2009; Trope & Liberman, 2010).

Initially, the construal level theory served as a framework for investigating psychological mechanisms, like planning fallacy and impulse control, while recently it has been applied in more interdisciplinary research, especially in consumer studies (Adler & Sarstedt, 2021). In this field, the construal level theory represents an effective explanatory model of the behavioural effects of customer's perceptions (Ding et al., 2021), shifts in consumption preference (Liberman & Trope, 2008), and purchase decision-making (Sun, Keh, & Lee, 2019). The most recent strands of applications of the construal level theory regard neuroscientific studies (e.g. Gilead, Trope, & Liberman, 2020) and societal issues, with a special focus on contemporary challenges as sustainability and climate change (e.g. Gao et al., 2021). The extant empirical research supports the construal level theory (Adler & Sarstedt, 2021). Most studies estimated a curvilinear relationship between abstraction level and psychological distance, independently on the dimension considered (Liberman et al., 2007). However, Sanchez et al. (2021) warn against excessive generalization of the relations found on limited samples, and Adler and Sarstedt (2021) recommend investigating each dimension of psychological distance deeper, in order to highlight its unique characteristics.

In fact, psychological distance is articulated in four interrelated dimensions: temporal distance, spatial distance, social distance, and hypotheticality (Adler & Sarstedt, 2021). Temporal distance is of particular interest for marketing studies, because it has been shown to bear an important influence on daily buying decisions of consumers (Cho et al., 2013; Ding & Keh, 2017). In general, the temporal construal theory suggests that the anticipation of the positive outcomes following the purchase (high-level construals) is more salient when the good is to be consumed in the distant future; conversely, the negative aspects related to the purchase (low-level construals) are more salient when the time of consumption is close (Liberman et al., 2007; Liberman & Trope, 2008) In particular, in consumer research, high-level construals refer to the characteristics making the consumption of a product desirable, while low-level construals indicate evaluations of the feasibility of the purchasing (Cho et al., 2013; Ding & Keh, 2017). The desirability of a product depends on the core benefits the customer expects from consumption, while feasibility relates to the cost of purchasing and using it (Trope et al., 2007). The empirical literature has confirmed that that the expected performance of a good is more influential in purchasing decisions from a temporally distant perspective, while the learning costs associated with using the product weight more from a proximal perspective (Castaño et al., 2008; Kim et al., 2009).

In the tourism and travel industry, the construal level theory has been applied to the investigation of the attitude of sharing tourist experiences (Lujun, Tang, & Nawijn, 2021), of destination choice (Ashioya et al., 2021) and various decision-making processes related to the tourist experience (e.g. Bornemann & Homburg, 2011; Kim, Kim, Kim, & Magnini, 2016; Jang et al., 2019; Jeong, Crompton, & Hyun, 2020). Most of such studies rely on experiments or questionnaires, which allow to explore the phenomenon in depth, but to the detriment of generality. To the best of our knowledge, the construal level theory has never been tested based on extensive and comprehensive databases, like prices published online, so far.

2.2. Dynamic pricing

To the aim of maximizing revenue, many companies sell similar products or services (more precisely, items having the same marginal cost) at different prices and are able to take profit from such strategy also in competitive markets, as noticed by the economic theory (Dana, 1998). This marketing practice is known as price discrimination. If the only element that differentiates goods is the time of purchase and their prices are set based on the past personal buying dynamic of each single customer, behavior-based price discrimination occurs (Caillaud & De Nijs, 2014). Whether the price of the otherwise identical items is the same for all buyers at the same time of purchase, but varies between different times of buying, intertemporal price discrimination is applied (Stokey, 1979; Abrate el al., 2019). Among intertemporal price discrimination practices, dynamic pricing consists in setting different prices for the same product, based on the booking time (Abrate, Fraquelli, & Viglia, 2012; Abrate et al., 2019).

Airlines and large hotel chains have pioneered dynamic pricing since the mid-Eighties, and many firms of the travel and tourism sector continue to play a starring role in such marketing strategy, that represents a viable solution to adjust their offer to market movements, given their stiff cost structure (Alderighi et al., 2015; Abrate et al., 2019). Nowadays, the technologies that allow to implement dynamic pricing efficiently have become more affordable also for small companies and this technique is spreading even among sharing economy platforms (Melis & Piga, 2017; Xie & Kwok, 2017; Oskam et al., 2018).

Most of the theoretical literature about dynamic pricing discusses the rationale of charging different prices over time from the perspective of the firm's organizational culture (e.g. Kalnins, 2016), its inventory controls strategies (e.g. Alderighi et al., 2015), the customer's perception of the price fairness (e.g. Choi & Mattila, 2018) or his/her willingness to pay (e.g. Tunuguntla, Basu, Rakshit, & Ghosh, 2018). The focus on the latter construct suggests investigating dynamic pricing empirically through models which interpret prices as measures of the buyer's willingness to pay for receiving the intrinsic value of a good, increased by the desired characteristics of the specific item under evaluation, and decreased by the perception of the sacrifice he/she has to bear for the purchase.

Almost all such empirical studies consider the advance booking period a deterministic explicative variable (i.e., a dummy or a count). This implies assuming that advance booking exerts a constant and proportional effect at any booking window. However, as pointed out by Cotteleer et al. (2008), hotel managers modulate their market power lever and preferences-based segmentation practices across advance bookings, thus, ignoring these factors in rooms rates modeling could lead to an omitted variable bias on the estimated shadow prices. with reference to hotel rooms. More recently, Lee (2018) has highlighted that a stochastic relation links prices posted by the same hotel for the same arrival day at different advance bookings and perceived quality, consistently with modern revenue management techniques, based on stochastic forecasting models of demand. Despite these warnings, very few studies explicitly consider that the relationship between price and revealed preferences could change along the booking window, since any product feature/attribute may become more (less) important for the consumer's choice, as the time of purchase approaches that of consumption.

To the best of our knowledge, only Abrate et al. (2019) and Guizzardi et al. (2020) have proposed a dynamic approach in this specific sense. In order to explain hotels' revenue, Abrate et al. (2019) measure the perceived quality of lodging by means of the average online review score, hotel class and post position, and monetary sacrifice with price changes counts and coefficients of price variation, along the advance booking windows. Their findings show that higher dynamic price variability leads to higher hotel revenues, supporting the effectiveness of dynamic pricing for revenue maximization. Guizzardi et al. (2020) account for the stochastic dynamic of room rates across advance booking periods directly, through a more complex panel Vector Auto-Regressive model. Their analysis shows that the hedonic value of time-invariant hotel attributes tends to increase as the advance booking period shortens. In this work, we move a step forward, by including also the time-varying quality score in the analysis, that leads to a possible interpretation of the model in terms of construal level theory.

2.3. Research hypotheses

In the light of the literature review above, we assume that the overall quality scores summarize the desirability of consumption. Then, by measuring the temporal distance with the days of advance booking, in this study we test the following research hypotheses:

H1: The overall quality score influences price positively.
H2: The influence of the overall quality score on price increases as the advance booking period lengthens.

In the hospitality industry, the firm size has been often used as moderator between price and quality. Some studies have found that larger firms offer higher room fares, likely because they tend to have higher star ratings and quality services (e.g. De la Pena, Nunez-Serrano, Turrion, & Velazquez, 2016). Yet, there is also opposite evidence, showing that hotel size can be inversely associated with perceived quality (e.g. Radojevic, Stanisic, & Stanic, 2015; Davronov, 2021). In fact, some studies link the difference in prices between large and small companies to their opposite marketing strategies: the former prefer to sell less rooms at higher rates, the latter aim to reach full occupation (e.g. Enz, Canina, & Lomanno, 2010). It has also been noticed that large firms offering prices lower that their rivals do not obtain comparable increases in room occupancy (Martinez-de-Albéniz & Talluri, 2011; Davronov, 2021). Thus, this topic deserves further investigation, also considering that a greater endowment of resources, typical of large firms, does not lead automatically to performance gains (e.g. Trainor, Andzulis, Rapp, & Agnihotri, 2014). In light of the extant mixed findings, we contribute to disentangle these issues, by testing the following hypotheses:

H3: The influence of the overall quality score on price in large hotels is higher than in small hotels.
H4: Both in large and small hotels the influence of the overall quality score on price increases as the advance booking period lengthens.

3. Study 1: Testing causality of the price-quality relationship

3.1. Materials and methods

To test whether a variation in the overall quality score determines a significant price variation (of the same sign) and, consequently, the price-quality relationship can be interpreted in terms of direct causality, we developed an online experiment with high behavioral realism, by measuring a form of real pricing behavior (see Viglia, Zaefarian, & Ulqinaku, 2021). More specifically, we took advantage from the preferential access to hotel revenue managers of an established vendor[1] of online booking systems, serving the accommodation industry, to administer an online questionnaire, prepared by the research team, to 304 Italian hotel managers. The first two questions are aimed at defining the base scenario:

- Please indicate the last price you posted on Booking.com for a standard double room for single use, 1 night stay.
- What was your hotel's overall quality score at the moment you published such price?

Then, simulating two alternative scenarios, managers were asked what price they would have set for the same room, all other conditions being equal, in case their hotel's overall quality score, at the moment they published such price, were one level[2] higher (e.g. 'Fabulous' instead of 'Very Good') or lower (e.g. 'Good' instead of 'Very Good'). To control for possible order-dependence of answers, half of the 304 managers received a questionnaire presenting the positive scenario before the negative one, for the other half the order of scenarios was inverted. The questionnaire included also questions about the socio-demographic characteristics of the respondent, and the main hotel features. The experiment was performed from January the 25th to February the 15th 2022.

3.2. Findings

Thirty-four managers provided valid and complete answers to all the questions. Sixteen respondents were presented the positive scenario first (i.e., hotel's overall quality score, at the moment they published the price, was supposed to be one level higher) and afterwards with the negative scenario (i.e., hotel's overall quality score, at the moment they published the price, was supposed to be one level lower). Eighteen were presented with the negative scenario first and afterwards with the positive scenario. Table 1 shows that most of the respondents hold a European Qualification equal to 5 (e.g. Higher National Diploma), that typically indicates that the professional has been working in the hotel sector for many years. Consistently, the most numerous age class is that of over 50, confirming that most respondents are well-experienced. The sample is balanced with reference to the hotels' star-rating. We record a slight prevalence of business hotels (58.8%), compared to the ones with mainly leisure clients (41.2%). This is likely due to the timing of the experiment (early February 2022, during the COVID-19 pandemic).

We test if the average room price, under the two simulated scenarios, is significantly lower or higher than the 81,2 euros per person/night observed (in the base scenario). We run two paired t-tests, designed to compare means from the same group under the two different scenarios. Results indicate that the price hoteliers would post on the Internet in case the consumers' rating were one level higher/lower is significantly higher/lower than the actually posted price (p-value $< 1\%$).

We acknowledge that under-coverage and non-response bias could be an issue with this kind of non-probabilistic sampling (the only possible design of experiment as we do not know neither the population contacts nor the socio/demographic characteristics of the "revenue managers" and we are forced, by budget and time constraint, to collect answers from self-completed questionnaires administered in February 2022).

However, we managed to limit and reduce these issues. Our sample is balanced with reference to the main factors we expect that may bias pricing decisions (hotels' star ratings and target segment), while a demographic screening reassures us that the characteristics of the respondents are also "unbiased", (see Table 1). Moreover, the respondents are heterogeneous in relation to the average price (room quality) and size of the property (room number). Not less important, the effect size in our experiment is quite big: the average difference in prices between the base and the positive/negative scenario are high and the sample variance is quite low. This increases the robustness of the results with respect to the sample size. Finally, in order to make our conclusion more robust to both selection bias and bias from non-observed heterogeneity, we bootstrapped one million t-scores, obtaining a minimum t-score of 2,64 (P-value $< 1\%$) for the positive scenario and a highest t-score of $-3,51$ (P-value $\ll 1\%$) for the negative scenario. All this considered, we can conclude that hotel managers determine prices (also) based on the observed online quality score and, thus, the relationship between quality and price is causal in nature.

4. Study 2: Testing the temporal construal theory on online prices

4.1. Data description

In order to test the temporal construal theory with reference to the relationship between product desirability (quality) and hotel prices, room rates for the same booking date must be observed for a repeated number of times, so that the trajectory of price variability at different temporal distances (as the check-in date approaches) can be explored. Prices and overall online ratings were scraped from Booking.com with Python package Selenium (through a code written specifically). Twenty-one daily queries were made for each of the 3–5 stars hotels in Venice, between midnight and 5:00 am, for limiting price changes during the scraping period. The data collection began on January the 7th, regarding check-in dates between that date and February the 29th, 2020 (day of the last query), but the observations prior to April the 1st were excluded from the analysis, as their advance-booking series was not complete. We considered early booking periods of 0 to 14 days, plus 28 and 56 days (chosen because they are both multiple of the number of days in a week). We did not scrape data for higher advance booking, in order to avoid losing a significant part of the observations (about earlier check-in dates, e.g. chosen a maximum early booking of 56 days, the first 56 observations must be discarded).

We searched for a single night reservation for one person (double room single use, not refundable fare breakfast included). Each query returns information on the best available rate for such a room as well as the quality score, which, however, varies only with the search date. In case no room with the specified characteristics was available, we reduced the bias that could be introduced by possible differences in the quality of the priced rooms, by using an auxiliary regression. This way, missing double room rates are estimated by means of a simple linear regression, where the independent variable is the observed price of a single room of the same hotel, for the same arrival day and advance booking. If both the intercept and the slope parameter of such simple linear regression are not highly significant (P-value lower than 1%), the missing datum is not imputed. An analogue procedure is used to estimate missing not-refundable rates when refundable prices (explanatory variable, in this case) are available. By contrast, missing rates with breakfast included are obtained either by adding the cost of breakfast to the published price, or by subtracting the cost of lunch, as we noted that these surcharge/discount rates stay the same for every hotel, arrival day and advance booking.

Among the 253 hotels initially sampled - which include the entire population of Booking.com Venetian hotels ranging from 3-star to 5-star category - we analyze the 102 accommodation firms for which less than 2% of the needed data is missing. The very few missing prices for the 102 hotels of the final sample were imputed by computing the arithmetic

[1] This vendor has collaborated with one of the researchers for a long time.

[2] We indicate shifts in quality level instead of in the numeric quality score, because the latter has a different effect on the quality level, and presumably on the consumer's perception, based on its starting value. E.g., if the current quality score is 7.9, then an increase of 0.1 does change the quality level from 'Good' to 'Very Good', but, if the current quality score is 8.0, then an increase of 0.1 does not change the quality level, that remains 'Good'.

Table 1
Descriptive statistics of participants in the online experiment and effect size (bottom- right grey panel).

Position	Count	European Qualifications Framework	Count	Age	Count
Revenue manager	5	5	17	20-39 y.o.	9
General manager/owner	21	6	9	40-49 y.o	10
Receptionist	8	7	8	50-69 y.o.	15
Total	**34**	**Total**	**34**	**Total**	**34**
Qualitysegment	**Count**	**Average quality**	**Average capacity (rooms)**	**Average Price**	**Prices' St.Deviation**
3-Stars	17	8,5	23,9	69,9	14,8
4-Stars	17	8,7	33,8	92,5	38,9
Total (base scenario)	34	8,6	28,8	81,2	31,5
Total (positive scenario: the consumers' rating is one level higher)				89,9	35,3
Total (negative scenario: the consumers' rating is one level lower)				72,5	30,7

Table 2
Descriptive statistics.

	Mean	Median	Standard deviation	Interquartile range
Rooms	42.29	27	47.38	21–50
	PRICES			
Hotels with more than 27 rooms	255.23	194.58	265.21	125.00–305.30
Hotels with 27 rooms or less	151.42	133.73	109.84	74.78–193.50
	OVERALL QUALITY SCORE			
Hotels with more than 27 rooms	8.6	8.7	0.503	8.3–9
Hotels with 27 rooms or less	8.4	8.4	0.621	8–8.9

	Relative Frequenceis 3 Stars	4 Stars	5 Stars	Restaurant	Meeting Room
Hotels with more than 27 rooms	35%	49%	16%	45.0%	33%
Hotels with 27 rooms or less	74%	26%	0%	13%	2%

average of the price published for the previous and the following dates, under the same advance booking. The resulting dataset includes 676,260 prices, published on Booking.com at 17 different lengths of advance booking for each date between January the 7th 2019 and February the 29th 2020 (390 check-in dates). We identified the last day of February 2020 as the closing date of the window because considering dates after the COVID-19 lock down announcements in the focal destination would prevent from getting a homogeneous dataset. However, as we set the maximum advance booking equal to 56 and included 3 lags of the dependent variable among covariates, the final dataset includes 331 check-in dates. Prices are denominated in euros and range between 13.91 and 739.50 euros, with a mean of 201.29 euros and a median of 157.50 euros. This positive asymmetry of the prices' distribution is due to few very expensive hotels present in Venice that contribute to make the arithmetic mean much higher than the median. Less expensive hotels charge less volatile prices: interestingly, in Venice, the variability of hotel prices increases with price levels over time. The highest peaks are concentrated between April and May, August and September, November and December, in proximity of the bank holidays or during the weekends.

The quality score is expressed on a scale ranging between 1 (very poor quality) and 10 (very high quality). With reference to our dataset, the minimum overall quality score is 6.9, the maximum is 10, the mean is 8.5 and the median 8.6. So, contrarily to prices, Booking.com online review scores are negatively skewed as found in previous research (Mariani & Borghi, 2018; Mariani, Borghi, & Gretzel, 2019). This evidence points out that not all the hotels that charge prices higher than the average offer a (perceived) quality higher than the average. The relationship between prices and quality is not linear, the highest prices are charged by hotels recording quality scores between 8.8 and 9.1, while lodging companies perceived as high-quality look very cheap. This evidence may indicate that this score tends to reflect also the consumers' expectation.

Table 2 displays some descriptive statistics comparing hotels with more than 27 rooms (our sample median) with smaller ones. Most small lodgings are 3 stars hotels and none vaunts 5 stars; larger ones are mainly 4 stars hotels. As expected, very few small hotels offer meeting rooms, while a third of the big ones do. The presence of a restaurant is much more frequent in large hotels, which generally supply a wider variety of services. This justifies that large hotels prices are on average 41% higher than small ones, with a percentage difference in the median rate equal to 31%, confirming an analogous finding by Sánchez-Lozano, Pereira, and Chávez-Miranda (2021) and Kim, Jang, Kang, and Kim (2020). The distribution of hotels by number of stars explains the larger variability of prices in large structures (standard deviation 59% higher than for small hotels), as higher stars hotels tend to be more expensive, and the number of stars is more variable in large structures. While differences in prices between large and small hotels are conspicuous, differences in overall quality score values are minimal. Large accommodation structures obtained slightly higher scores, however the standard deviation of overall quality ratings for small hotels is 23% higher. Room rates and quality are much more correlated in large hotels, suggesting that their managers are more effective in retrieving a premium price from quality improvements.

Looking at Fig. 1 and Fig. 2, it is apparent that overall quality scores change more slowly and to smaller extents than prices. In fact, hotel managers can modify prices much easier and faster than they can increase service quality, in response to market movements. The impact of any service change on the consumers perceived quality, and thus on prices, is uncertain.

As displayed in Fig. 3, on average, percentage change in rates by advance period are greater in large hotels. This suggests that advance-

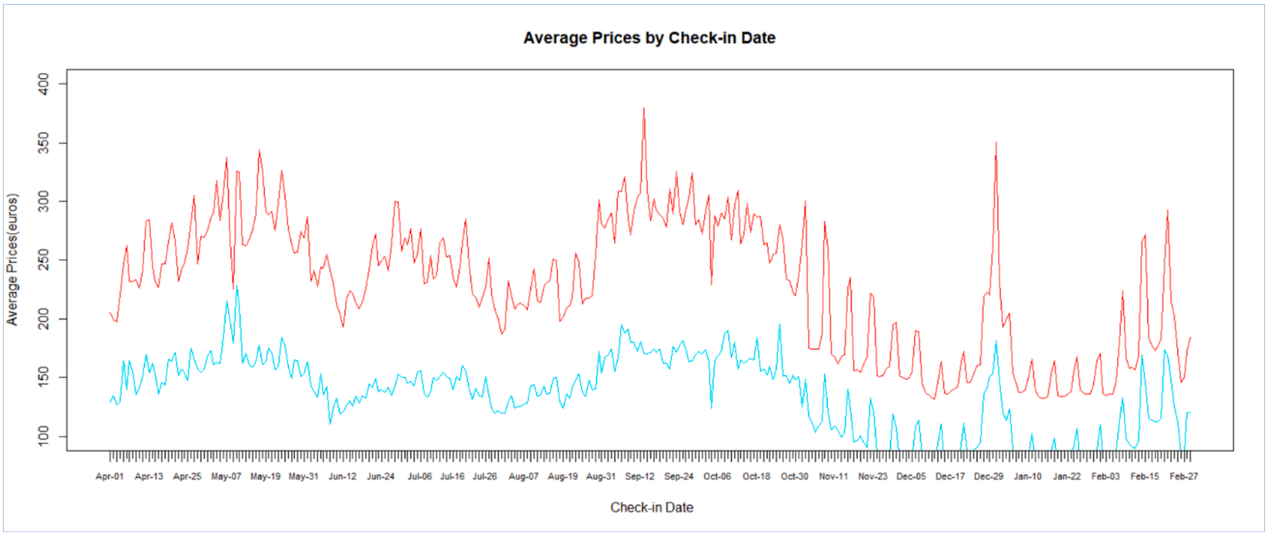

Fig. 1. Average price by date.

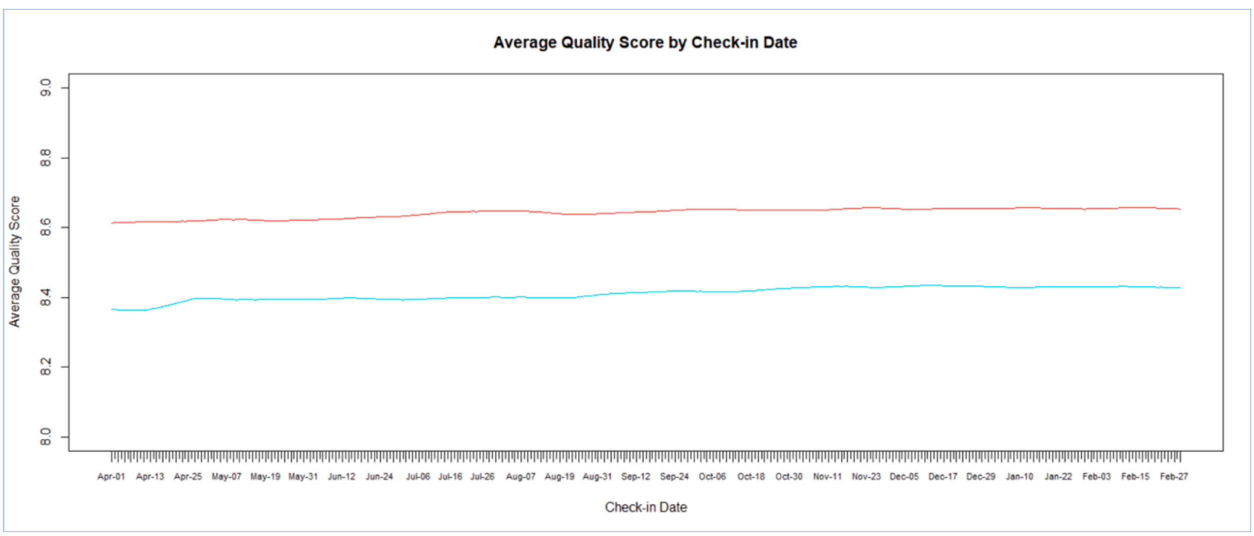

Fig. 2. Average quality score by date.

Fig. 3. Average price by advance booking days.

book-based dynamic pricing strategies are mainly employed by large hotels' managers. In small hotels room rates increase almost imperceptibly as the advance augments, with a slight acceleration after 2 weeks, outlining a very cautious pricing profile. In large hotels, prices peak at 1 week and 2 weeks of advance bookings, then, room rates stay high for longer periods.

4.2. Model specification

We adopt a semi-parametric approach, estimating the relationships outlined in the research hypotheses (that are causal in nature in the online experiment) non-parametrically, because, currently, the construal theory applied to dynamic pricing does not supply precise indications about the functional form of the relationship between prices, advance booking and quality score. Therefore, we let the available data draw such relation, without imposing distributional assumptions. Then, we follow the common practice of specifying a linear relationship between the natural logarithm of price and the dummy variables expected to signal peak periods (e.g., Abrate et al., 2012), as well as the following five site and situational attributes (e.g. Guizzardi et al., 2020)

- Number of Stars,
- Presence of at least one Restaurant (dummy variable),
- Availability of at least one Meeting room (dummy variable),
- Distance (meters, in logarithm) from the access point to Venice (the Central train station of Santa Lucia that is also near to the main parking sites and Roma square bus hub),
- Distance from San Marco square (the main attraction, meters in logarithm).

Logarithms are generally applied to prices for interpreting coefficients as percentage changes of the dependent variable given a unitary increase in the correspondent explanatory variable. Combining the parametric price dynamic with the non-parametric estimation of the relationships we intend to test (H1, H2, H3, H4) in a varying coefficient model (Hastie & Tibshirani, 1993), we estimate the following function:

$$\ln(P_{t,k,i}) = c + Seas_{t,i}\gamma + \ln(P_{t-1,k,i})\varphi_1 + \ln(P_{t-2,k,i})\varphi_2 + \ln(P_{t-3,k,i})\varphi_3 + Q_{t-1,k,i}\beta_k + X_i\delta + \varepsilon_{t,k,i} \quad (1)$$

where $P_{t,k,i}$ is the price posted by the i-th hotel for the check-in date t reserved k days in advance. c is a constant term, $Seas_t$ is a row vector composed of 4 dummy variables: one indicating weekends (Friday and Saturday), one for August, one for bank holydays, and one for Venice events. The coefficients representing the linear effect of these dummy variables on prices (in logarithm) are piled in vector γ. $\varphi_1, \varphi_2, \varphi_3$ are the coefficients that capture the time association between prices of the same hotel at the same period of advance booking, 1, 2 and 3 days apart respectively. X_i is the row vector of site and situational attributes with coefficients δ. $Q_{t-1,k,i}$ is the first lag, in logarithm, of the overall quality score that a customer sees online on day t-k for the hotel charging $P_{t,k,i}$. All the considered explanatory variables are exogenous, also the (non-lagged) quality score (Wu-Hausman test: chi-squared statistic 10.27, P-value 0.136%). However, for making sure to avoid any possible endogeneity issue, we used the first lag of the overall quality score, which is computed by Booking.com from individual user generated scores. β_k is the coefficient that represents the causal relationship between quality and price at the k-th advance booking period. It is estimated as a linear smoothing spline of each advance booking period (effect modifier), by minimizing the following equation:

$$\sum_{i=1}^{N}\sum_{t=1}^{331}\left[\ln(P_{i,t}) - \sum_{k=1}^{17} Q_{t-1,k,i}\beta_k(K)\right]^2 + \sum_{k=1}^{17}\lambda_k\int_0^1\left(\beta_k^{(I)}\right)^2\delta k \quad (2)$$

where $N = 102$ is the number of hotels. λ_k are non-negative smoothing parameters (representing the constraints on the derivatives, necessary for the optimization) and $\beta_k^{(I)}$ is the first derivative of β_k. Overall, this model keeps the ease of coefficients interpretation of a linear regression, but it allows coefficients varying over advance booking days with the flexibility of a non-parametric method.

4.3. Findings

4.3.1. General model estimation results

We start by estimating equation (1) on the full sample. As a preliminary check, we estimated a 'full' varying-coefficient model, allowing all the coefficients to change as a function of the days of advance booking. We found that all the variables' coefficients, except for quality, remain unchanged at different advance booking periods. Consistently, the site and situational attributes, and the autoregressive movement of prices reflect the invariant objective characteristics (and cost structure) of each single hotel. The, deterministic, seasonality effect on prices also results time-invariant. Therefore, we re-estimated the model with fixed coefficients for the time-invariant effects, as described in equation (1). The estimation output is reported in Table 3. In Fig. 4 the estimated values of the β_k coefficients are displayed: they quantify the influence of the quality score on price, as a smoothed function of the days of advance booking. The degree of smoothness is expressed by the estimated degrees of freedom (edf), a monotonic decreasing function of the lambda parameters in Eq. (2). The higher the edf, the less smoothed the curve (see: Cantoni & Hastie, 2002). We also report the F-statistic, based on which the significance of the varying coefficient is assessed.

All the explanatory variables are significantly correlated with prices and, overall, they account for 53.2% of its variability, a satisfying result when modeling very volatile dependent variables. The Generalized Cross Validation (GCV) prediction error criterion is reassuringly small, thus we can deem this model useful to test our first two research hypotheses.

Estimates suggest that seasonality is essentially stochastic, as the autoregressive coefficients sum to 0.677. We tried different lag structures and found that the proposed one, including three lags, is significant and associated to the best value of the Akaike information criterion. The first lag of the log-price looks especially important, as it determines (on average) 32.1% of the 'current' room fare, a result in line with Soler et al. (2019). The deterministic seasonality appears to exert a marginal, although highly significant, effect. During weekends room fares are 5.3% higher, while during the bank holydays they increase by 1.7%. As

Table 3
Estimation results – full sample.

Variable	Estimate
(Intercept)	−0.259***
Weekends (WE)	0.053***
Events	0.018***
August	0.020***
Stars	0.161***
Restaurant	0.065***
Meeting room	−0.024***
Distance train station	−0.002*
Distance San Marco	−0.019***
Bank Holidays (BH)	0.017***
log price Lag1	0.321***
log price Lag2	0.173***
log price Lag3	0.183***
Quality Score:	
EDF (smooth term)	10.42
F-statistic	353.7***
Adjusted R-square	0.532
GCV prediction error	0.242

'***' P-Value < 0.001 '**' P-Value < 0.01 '*' P-Value < 0.05.

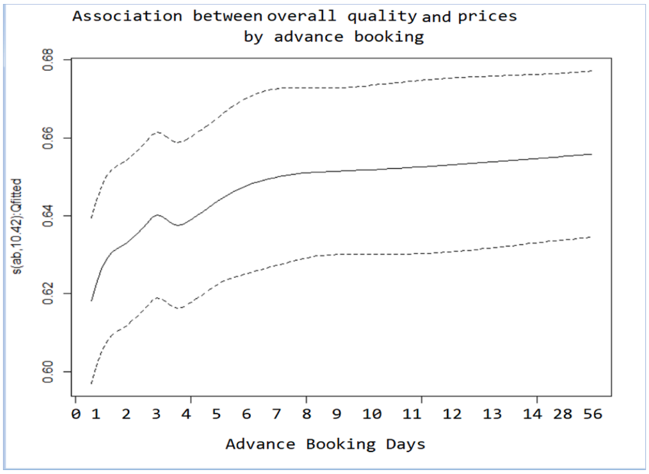

Fig. 4. Dynamic of the association of overall quality and prices by advance booking days.

the average observed price is 201 euros, the estimated average increase of rates due to the deterministic effect ranges from the 3.42 euros (average discount for bank holidays) and 10.65 euros (average overprice for weekends).

Looking at the price-quality relationship, since equation (1) is a log-log specification, the estimated coefficients (see Fig. 4) are "elasticities". An increase of 1% in the quality score determines a growth by 0.619% and 0.657% in room rates for last-minute booking and reservations made 56 days in advance respectively. In absolute terms, a unit increase in the average quality score causes an average overpricing ranging from 15,1 euros (7,3% for the shortest k) to 16,1 euros (7,7% for longest k), a result in line with Viglia, Minazzi, and Buhalis (2016). Overall, the influence of quality on room fares is positive, thus H1 is supported by our findings, as anticipated by the online experiment.

Moreover, β_k values increase as the advance booking period lengthens, so H2 is also supported. Overall quality also shows a positive effect on price for last-minute booking, but as the temporal distance between purchasing and consumption increases, this effect becomes larger and larger. This finding is consistent with the construal level theory, as well as with the results of previous studies (Bornemann & Homburg, 2011; Do & Kim, 2012; Fu, Cheng, Bao, Bilgihan, & Okumus, 2020).

4.3.2. Estimation results by hotel size

Micro and small tourism enterprises have difficulties in the adoption of interoperability solutions (Reino, Alzua-Sorzabal, & Baggio, 2016). For example, they can hardly integrate the central reservations system with the property management system (PMS) in order to apply effective dynamic pricing or, in case they offer a restaurant or café, to know how much money a guest spends. The scarcity of information and communication technology (ICT) applications specifically designed for small enterprises, can also prevent from improving the overall quality of the guest experience. In fact, modern ICT systems allow to manage guests' needs (e.g, reschedule and reprioritize housekeeping tasks or a personalize the catering) from a centralized command-and-control center where the different hotel functions are integrated. These considerations led us to investigate whether the temporal construal theory holds for both large and small hotels (H4).

Thus, we re-estimated equation (1) on the subsample of large hotels and on that of small hotels separately. We classified among large hotels those with a number of rooms higher than the median (27 rooms), while the remaining firms form the other subsample. The results of the two separate estimations are shown in Table 4. Our varying coefficient model fits large hotels data much better, as indicated by an R-square of 0.592, while that for small hotels equals to 0.354. This indirectly suggests that large hotels apply 'coded' pricing schemes which, as such, can be modeled more successfully. Consistently, the prediction error is lower for the sample of large hotels. By comparing the EDF, we notice that the dynamic of the association of quality and price by advance booking is more smoothed for large hotels.

Table 4
Estimation results by hotel dimension.

Variable	Estimates		
	LARGE hotels		SMALL hotels
(Intercept)	−0.778***		0.154 ***
Weekends (WE)	0.069***		0.037 ***
Events	0.034***		0.004
August	0.016***		0.024 ***
Bank Holidays (BH)	0.030***		0.006 *
Stars	0.166***		0.139 ***
Restaurant	0.052***		0.028 ***
Meeting room	−0.043***		0.016 *
Distance train station	−0.003*		0.009 ***
Distance San Marco	−0.029***		0.012 ***
log price Lag1	0.332***		0.304 ***
log price Lag2	0.178***		0.163 ***
log price Lag3	0.183***		0.176 ***
EDF (smooth term)		9.886	9.290
F-statistics		232.4 ***	160.6 ***
Adjusted R-square		0.592	0.354
GCV prediction error		0.220	0.259

'***' P-Value < 0.001 '**' P-Value < 0.01 '*' P-Value < 0.05.

Looking at the estimated values of the coefficients for the lagged (log) price, room rates are more time-correlated in large hotels, suggesting that large hotel properties apply dynamic pricing strategies that are more consistent with the intra-week seasonality. Furthermore, the great importance of past prices in explaining the current levels may hint a possible higher attention to consumers price fairness issues (see: Choi & Mattila, 2018). Large hotels apply also larger price increases during the demand peaks, that characterize weekends, bank holidays and, above all, cultural events. Therefore, during events, like the famous Venice Biennale, characterized by the inflows of groups, net to the effect of other variables, large hotels have a competitive advantage of almost 8.7 euros. Other average differential contributions to price (between large and small hotels) are almost 12.0 euros for weekend and 7.6 euros during Bank Holidays. Conversely, small hotels set higher premium prices during August, when the composition of demand (mainly leisure and low-medium income) increases above all for cheaper lodgings.

Focusing on the price-quality relationship (see Figs. 5 and 6), we note that it is sharply different between small and large hotels. The estimated varying coefficients range between 0.861 and 0.882 in large hotels, and between 0.40 and 0.452 in small hotels, but the curve of the influence of overall quality on prices by advance booking is steeper for the latter. This evidence suggests that the effect of the overall quality score on price in large hotels is greater than in small hotels, at any advance booking, thus H3 is supported. We also note that this difference is particular evident in absolute terms as – for example considering the last minute – a unit increase in the average quality score determines averages overpricing of 7,1 and 25,5 euros (for the small and large hotels respectively).

In both cases, the price "elasticity" to quality increases as the temporal distance increases, thus the temporal construal theory holds for both subsamples and H4 is supported. The fact that, in small hotels, the influence of the overall quality score on price decreases sharply for last-minute reservations, confirms the important role played by last-minute discounts for such companies (see Martinez-de-Albéniz & Talluri, 2011; Guizzardi, Pons, & Ranieri, 2017), that have less resources available for differentiating the product.

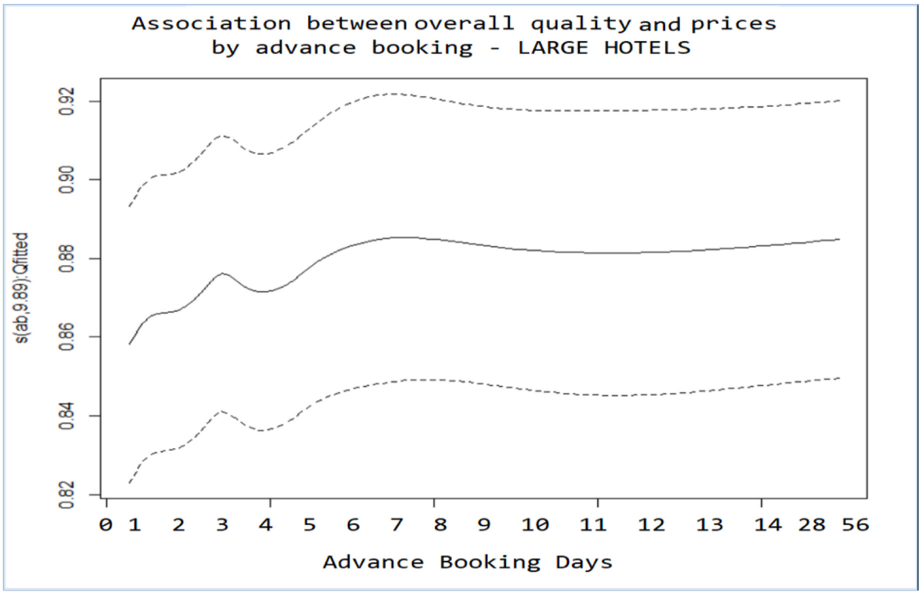

Fig. 5. Dynamic of the association of overall quality and prices by advance booking days in large hotels.

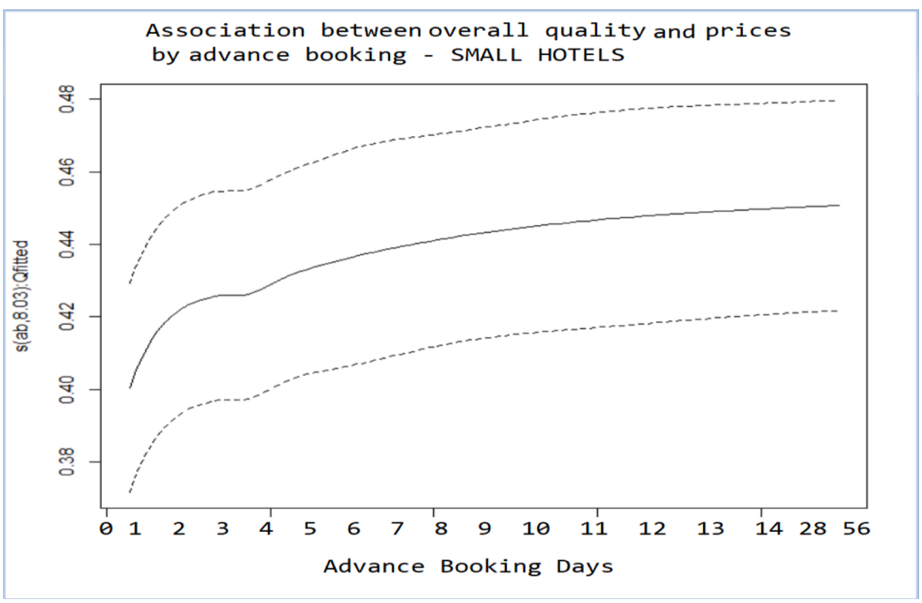

Fig. 6. Dynamic of the association of overall quality and prices by advance booking days in small hotels.

5. Discussion and conclusion

When evaluating a product, consumers may interpret price information as both a signal of quality and an indicator of monetary sacrifice. Through an online experiment (Study 1), we showed that there is a causal relationship between quality and price, as hotel managers modify room prices based on the online quality score, ceteris paribus. Then (Study 2), by using panel data about prices and ratings published online by 102 hotels in the worldwide famous destination city of Venice (Italy), we modeled the complex relationship between prices and online customer ratings in light of the temporal construal theory (Liberman & Trope, 2008). According to such theory, the quality (desirability) of a product becomes more influential, in the customer choice, as the temporal distance increases. By assuming that the overall quality score summarizes the desirability of the product and measuring the temporal distance between purchase and consumption through advance booking, we found that the overall quality score influences price positively and that this effect increases as the advance-booking period lengthens. Thus, we showed that the temporal construal theory can represent a sound interpretative framework also to explain the usefulness of dynamic pricing, with reference to hotel overnight stays.

Then, we investigated if the temporal construal theory applies regardless of firm size, looking at to both large and small hotels, by estimating our varying coefficient model for each size-based group of firms separately. This way we provided further evidence of the validity of the temporal construal theory, as a psychological interpretative framework, in both cases.

5.1. Theoretical and research contributions

To the best of our knowledge, so far, the extant literature about dynamic pricing has never employed a behavioural psychology theory as an interpretative framework of the effectiveness of such a pricing strategy. Thus, the main innovative contribution brought about by this study consists in the pioneering investigation of the appropriateness of the temporal construal theory to interpret the effectiveness of dynamic pricing in the hotel sector. We also extended the analysis to firms with different size and thus with different availability of resources.

A second contribution of this paper is represented by the finding that the effect of quality on room rate decreases much more sharply for last-minute reservations in small hotels, confirming the key role played by last-minute discounts for such structures, having less resources available for differentiating the product.

Another result of interest for the marketing literature derives from modelling both stochastic and deterministic components of the effect of demand peaks on price. This allowed us to find that this relationship is mainly stochastic, as suggested by Croes and Semrad (2012). The relative magnitude of the estimated autoregressive coefficients strengthens the finding by Soler et al. (2019) that the price of the previous day is the most important explanatory variable for the current price. This evidence is stronger for large firms and suggests that they apply dynamic pricing strategies that are more consistent with the intra-week seasonality, or that they tribute a greater importance to consumers price fairness issues (see: Choi & Mattila, 2018). The significance of the deterministic component of the seasonality is in line with the finding by Herrmann and Herrmann (2014). However, we extend previous research by finding that both the autoregressive dynamic of prices and the deterministic seasonal pattern remains unchanged at different advance booking periods, as, to the best of our knowledge, so far not study addressed the possible variability of the prices dynamic at different advance booking windows.

Besides the above findings, our time-varying model brings some evidence regarding the correspondence of peak and shoulder season dates with dynamic pricing practices. Specifically, we showed that large hotels tend to charge a premium price during weekends, events and bank holidays, while small structures apply discounts.

With reference to the methodology employed, this is the first study where the advance booking time is modelled as modifier of the effect of quality on prices. In order to do this, we employed a very flexible model, allowing to combine parametric and non-parametric components, but retaining the ease of interpretation of a simple linear regression. Estimating a varying coefficient model is a simple, objective and transparent method to detect the relationship between prices, quality and advance booking, controlling for seasonality. In particular, by capturing both stochastic and deterministic components of seasonality and accounting for the days of advance booking, we augment the model with some components typical of revenue management practices and that we believe should be considered by revenue managers. The new method proposed in this study can enhance future research methodology approaches to dynamic pricing research, which can be conducted on the data publicly available on online travel agencies' web sites.

5.2. Practical implications

Our findings bear important implications for managers involved in dynamic pricing. First, the claim that the expected quality of a product is more influential in purchasing decisions made from a temporally distant perspective is supported in our dynamic pricing setting. Overall, our research shows that, when evaluating a product, consumers interpret price information as an indicator of quality especially at higher advance bookings. This result strengthens the findings by Jang et al. (2019), Zhang and Kalra (2014) and Fu et al. (2020) that clients who make reservations last-minute base their choice mainly on the room rate level and look for discounts, as opposite to those who book earlier, whose decisions are driven rather by the assessment of amenities. Thus, efforts made to communicate service quality (i.e. to differentiate the product offered by leveraging the hotel or rooms' characteristics) lead to the opportunity to ask for a premium price mainly at long advance booking periods.

However, the relationship between quality and price is not linear and tends to flatten after a week of advance booking. While most of the extant empirical literature found a curvilinear relationship between abstraction level and psychological distance, independently on the dimension considered (Liberman et al., 2007), our analysis supports a relationship that is more jagged within a week from check-in and almost flat for earlier times of reservation. Although it may be argued that the inclusion of further advance booking lengths in the database could have led to the estimation of a different shape, the evidence that the function becomes monotonic after about a week of advance booking (see Figs. 4, 5 and 6) is quite reassuring of the opposite. Intuitively, we might acknowledge that the difference between booking a month in advance and booking earlier does not change the perception of the distance from the moment of consumption as the difference between making the last-minute reservation and booking within one week does, as it has been shown by previous studies (Kim et al., 2016; Jang et al., 2019). Moreover, as highlighted by Adler and Sarstedt (2021), each dimension of psychological distance is characterized by unique traits, that manifest differently in different decision-making contexts and, to the best of our knowledge, this is the first investigation focusing exclusively on the temporal distance in hotel rooms dynamic pricing. Thus, further studies of this dimension, in this field, are needed to strengthen our results, which, however, point to what could be turn out to be an interesting peculiarity of this sector.

Second, the evidence that, in this destination targeting mainly the cultural and inbound segments, guests who reserve later might not be willing to pay a premium price for a quality improvement implies that discounts and price promotions should be effective especially for last-minute selling, in line with previous studies about other market segments (Bornemann & Homburg, 2011; Jang et al., 2019; Jeong et al., 2020). Since late booking guests are less sensitive to quality, managers in charge of dynamic pricing should find it worth offering high quality rooms at long advance booking at higher prices, and low-quality rooms for late reservations with price discounts. This suggestion is consistent with the "old good revenue management rule" to sell the best rooms first (Escoffier, 1997). In fact, if high quality rooms are not sold with long time of advance, it remains only the possibility to sell them with shorter advance, increasing the risk of a greater loss in revenue than a low-quality room left unsold.

It is worthy to note that we found that the influence of the overall quality score on price in resource-aboundant large hotels is higher than in small hotels, but the difference is not that great. Based on previous studies (PATA, 2014; McEvilly, 2015; Guillet & Law, 2019), we expected this result, because large hotels usually own enough resources to implement dynamic pricing with sophisticate technologies and skilled personnel. On the opposite, small lodgings, might have difficulties in pricing quality, managing guest loyalty and/or improving the overall quality of the guest experience (Reino et al., 2016). However, our results confirm that this IT gap is progressively disappearing, possibly thanks to the increasing affordability of such technologies (Melis & Piga, 2017; Xie & Kwok, 2017; Oskam et al., 2018), thus, intertemporal price discrimination is becoming an effectively employed strategy also in small lodging firms (Melián-González, Bulchand-Gidumal, & González López-Valcárcel, 2013; Mellinas & Martin-Fuentes, 2019).

Our investigation of the dynamic relationship between online quality ratings and prices yields relevant implications also for hotel reputation managers. In particular, we highlight that the overall quality score has a great impact on room rates, implying that an effective online communication management strategy is crucial for obtaining higher user ratings and, consequently, being able to charge a premium price. However, web reputation management is complex and difficult, because managers have little control on it. Due to the open nature of web reputation, managers cannot anticipate what interactions, reviews and ratings will shape it, thus they can have to face negative reviews and shifts in quality ratings they are not prepared to (Paschke, Alnemr, & Meinel, 2010). For example, Proserpio and Zervas (2017) found that when hotel communication managers start responding to negative reviews, then they tend receive fewer but longer and more detailed negative reviews. Therefore, hotel managers should invest in vocational training on the professional use of social media features, in order to seize the value created by service quality improvements. However, since we have shown that price "elasticity" to the quality score is higher in large hotels, managers of large accommodation structures in Venice might find it more profitable to focus on reputation management than those of small hotels. The latter tend to compete by offering discounts, especially for last-minute reservations (see: Martinez-de-Albéniz & Talluri, 2011; Guizzardi et al., 2017), a result that might also be explained by the high affluence, in Venice, of tourist groups, that cannot be accommodated in small structures.

5.3. Limitations and research agenda

This study is not without limitations. First, with reference to Study 1, under-coverage in the sampling frame and non-response bias could potentially limit our inference. In this case, a systematic sampling design, starting from the definition of the sample size for the desired precision and significance level, was not possible, because the reference population (hotels for each star rating), and auxiliary variables (how many female revenue managers, how many for each age class, etc.) are not known. Moreover, hotel managers themselves decided whether or not to respond to the questionnaire, thus we relied on availability (instead of random) sampling. As a consequence, independently on the sample size, the risk of self-selection bias is unavoidable. However, our sample is balanced with reference to the hotels' star ratings, target segment (leisure/business) and rooms quality, which are the main factors that may bias pricing decisions, because they are generally highly correlated with price. Moreover, the sample variance is very low, the average difference in prices between the base and the positive/negative scenario is far from zero, the *t*-test is performed on pair samples, we checked the distribution of one million bootstrapped t-scores for each scenario, so our conclusion that the price-quality relationship is causal in nature can be considered robust, even if sample bias – that can be common in marketing experiments (see Viglia et al., 2021) - cannot be excluded.

Second, we focused on a sample of hotels drawn from a specific cultural and leisure destination, characterized by strong incoming demand and over-tourism problems. Further studies might collect data from other destinations to validate our findings and make them more generalizable, also in light of different cultural factors across destinations (Mariani, Borghi, & Okumus, 2020). Third, we sampled medium and higher-end hotels (i.e, three-star, four-star and five-star) also to control for potential confounding effects generated by different levels of customer expectations when taking into account different features of hospitality firms' marketing, reputational, and managerial issues (Park & Allen, 2013; Mariani & Borghi, 2020), which coincide with different levels of customer satisfaction and online review ratings. Future research might look at budget hotels (such as one-star and two-star) as well. Moreover, we focused on a specific set of hospitality firms (hotels), without considering other hospitality firms, such as sharing economy accommodation solutions, like Airbnb, which increasingly engage with dynamic pricing (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018). Future research might investigate if the detected findings can be extended also to accommodation providers beyond the hotel sector. Furthermore, we have confined our attention to a discrete and parsimonious set of explanatory variables. Future research might generate a richer specification, including other explanatory variables, such as user generated ratings regarding specific hotel features like service robots (Mariani & Borghi, 2021), or moderating effects such as online review submission devices (Mariani, Borghi, & Gretzel, 2019) and online reviewers' experience (Mariani & Predvoditeleva, 2019). Finally, future studies employing the construal level theory for investigating the impact of the social distance and hypotheticality of online ratings on the hotel choice might be of special interest. In fact, quality scores are provided by former guests that are unknown to the decision-maker and the electronic processing they undergo might influence their perceived reliability.

CRediT authorship contribution statement

Andrea Guizzardi: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Marcello M. Mariani:** Conceptualization, Formal analysis, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. **Annalisa Stacchini:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

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

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