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Advance booking across channels: The effects on dynamic pricing

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ABSTRACT

This research analyzes the effects of advance booking and channel type on hotel rates. While this relationship has been addressed in the literature, most studies take a partial approach by focusing only on one distribution channel or one destination. This study fills this gap by analyzing the price dynamics for four channels and multiple destinations. The data set consists of 39,363 bookings for 1085 hotels over 27 consecutive months. We used two-stage least squares to solve potential endogeneity issues, and the results proved that distribution channel, hotel type and hotel size have an influence on the effect of advance booking on hotel rates. Critical managerial implications are discussed.

1. Introduction

Advance booking is one of the most controversial issues in tourism (Nicolau & Masiero, 2017). Its implications for pricing (Schwartz, 2008), revenues (Abrate, Nicolau, & Viglia, 2019), and timing (Zhang, Liang, Li, & Zhang, 2019) are challenging for practitioners and researchers. The strategic value of advance booking for hotels was highlighted by Guizzardi, Pons, and Ranieri (2019) and its importance has been heightened due to the advent of digital technologies and multiple booking channels (Murphy, Chen, & Cossutta, 2016). This new scenario, characterized by an omnichannel setting where tourists search different sources and suppliers (Mahrous & Hassan, 2017), is becoming more important; it has been identified also as a key research topic in other retail fields (Verhoef, Kannan, & Inman, 2015). Essentially, omnichannel retailing involves customers moving between different channels during their searches, which has drastically changed their decision-making processes in the last years. As the Sitel Group (2018) noted “the path to purchase for a Club Med vacation is 96 days and on average features 11 digital and physical touchpoints”.

Hospitality and tourism researchers have intensively analyzed the effects of hotel room rates and their determining factors (see Masiero, Nicolau, & Law, 2015). Advance booking and pricing have been addressed in the literature with different approaches, through surveys, experiments, and modelling (Zhang et al., 2019). Interestingly, studies based on multiple types of channels, intermediaries (i.e. online travel agencies) and direct channels (i.e. hotel websites), and using real data from multiple destinations, are scarce (Zhang et al., 2019).

The aim of this study is to analyze the effect of advance booking on hotel rates across four channels, hotel websites, online travel agencies (OTAs), call centers and global distribution systems (GDSs), using real data collected over 27 months from multiple Spanish destinations. For this purpose, we estimate four regression models, using two-stage least squares to control for potential endogeneity. These models address three research questions: First, is there any price dispersion in advance bookings by channel type? Second, does the hotel type -urban vs resort- have an influence on the effect of advance booking on hotel rates? Third, does hotel size exert an influence on the effect of advance booking on hotel rates?

Our study includes multiple destinations, with 39,363 observations at 1085 hotels, collected over 27 consecutive months on 4 different booking channels. This multi-destination approach allows us to better generalize the results and the use of more than one year of data permits controlling for seasonality. Note that previous studies examined only one destination (Guizzardi et al., 2019; Masiero et al., 2015; Nicolau and Masiero, 2017; Yang, Jiang, & Schwartz, 2019), using data collected over less than one year (Guizzardi et al., 2019), a limited number of sources (Murphy et al., 2016; Yang et al., 2019) or examined multiple channels with surveys (Chen & Schwartz, 2008; Mahrous & Hassan, 2017; Murphy et al., 2016; Jang, Chen & Miao, 2019), experiments (Rahman, Crouch, & Laing, 2018), or modelling (Guizzardi et al., 2019; Zhang et al., 2019). Interestingly, Abrate, Fraquelli, and Viglia (2012) examined three months of real data but only from one OTA (Venere.

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com), eight urban destinations and 916 hotels, which resulted in a generalized linear model. Thus, our study contributes to the extant knowledge by expanding the number and diversity of distribution channels (hotel websites, OTAs, call centers and GDSs), the number and types of destination (e.g. urban versus coastal), the period of analysis to 27 consecutive months, and by using real data. We further analyze the effect of advance booking across different distribution channels on hotel rates by simultaneously examining the impact of hotel type and hotel size, and controlling for quality of hotel, seasonality of the destination and length of stay. The analysis was conducted using 2SLS to control for potential endogeneity between hotel rates and advance booking.

The overall approach of this study is based on identifying the underlying conceptual roots of advance booking in an omnichannel setting. This approach is in line with MacInnis (2011) identifying of conceptualizations and is also in line with recent views on the theories-in-use approach suggested by Zeithaml et al. (2020).

This research contributes to the literature by analyzing the impact of omnichannel behavior on the effect of advance booking on hotel rate. From the practitioner's viewpoint, the study's findings might guide hotel managers in their pricing strategies over time and by hotel type (e.g. size, quality and location). Lastly, consumers can learn the underlying pricing strategies of hotels by channel which, in turn, might help them in their advance booking behavior.

2. Conceptual framework

2.1. Omnichannel pricing over time

Tourist advance booking refers to purchasing a product or a service before the time of consumption. In advance booking, tourists typically search for an economic (e.g. lower price), or security (e.g. book to avoid lack of availability) incentive. This issue impacts more in hospitality than for tangible products because of the scarce, or limited, availability of offers over any given period of time.

From a managerial perspective, dynamic pricing by hotels and intermediaries is gaining momentum due to the increasing complexity of combining pricing policies over time in a dynamic scenario. Moreover, multichanneling adds complexity. In turn, managers are adopting dynamic pricing which is constrained by the digital transparency of prices. This new multi-channel setting needs further research as regards advance booking and accommodation prices. As Neslin et al. (2006, p. 96) stated, "multi-channel customer management involves the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development". The recent literature has suggested adding the interplay between channels and brands, in what is termed omnichannel behavior (Verhoef et al., 2015). A particularly interesting question in hospitality now is how will hotel managers cope with pricing and time in this omnichannel setting. This new scenario, named omnichannel pricing over time, involves several key factors: pricing, time, customer expectations, channel interchange and type of hotel.

2.2. Theory of price dispersion

Price dispersion refers to the price range for the same item across sellers. Price discrimination is a strategy of charging different prices in different channels that result in price dispersion (Kim, Cho, Kim, & Shin, 2014; Yang et al., 2019). Price discrimination is a key tool for hotels to help them control uncertain demand (Chen & Chang, 2012; Chen, Chang, & Langelett, 2014) or successfully manage their channels (Kim et al., 2014). Price dispersion can be approached from two angles, by channel and by time.

Price dispersion by channel is affected by the digital setting where tourists may search and compare through online platforms. Furthermore, online aggregators (e.g. Kayak) foster a more transparent market (Bigné & Decrop, 2019). However, this new scenario assumes that tourists are aware of the different online platforms and spend an unlimited time at a low information search cost to find the best deal (Yang et al., 2019). In such a scenario, the pricing structure of hotels and intermediaries is *nearly* transparent to the customer, as Carroll and Siguaw (2003) pointed out. Since price dispersion may reflect a hotel's pricing strategy, different actions -regardless of potential rate-parity agreements-may affect pricing convergence. These actions might be: (i) a limited number of lower-priced rooms are allocated to one channel or platform in an attempt to attract tourists' attention; (ii) price changes due to browsing history using cookies (Time, 2017); (iii) a one-day limited offer, "deal of the day" or similar sales promotion; (iv) customized offers based on retargeting.

Price dispersion over time in hotel bookings involves a continuum from early-bird bookings to the last-minute deals that lead to dynamic pricing strategies (Abrate et al., 2012) that maximize short-term revenue (Yang & Leung, 2018). However, the literature has identified that, in some locations, such as Mediterranean hotels, OTAs prefer uniform pricing over time (Melis & Piga, 2017); in addition, Abrate and Viglia (2016) found less price variations over time, subject to the level of competition. Overall, the literature shows that OTAs' and hotels' optimal pricing policies over time depend on type of customer, star rating and the number of suppliers with available rooms (Abrate et al., 2012). They also depend on financial issues, such as unit sale commission, service cost, multiple destinations, longer time periods, and hotel-related factors, such as size and quality, by different channels and multiple providers or platforms. Therefore, price dispersion over time still needs further research because of limited capacity, perishable assets, omnichannels, time-related pricing, and the rapid growth of the Internet and global distribution systems in the lodging industry.

2.3. Customer expectations over time

In advance booking, customer expectations are driven by two main factors, price variability and unavailability of rooms (Schwartz, 2008). Most of the conceptual approaches toward analyzing customer expectations and advance booking are focused on valid but general assumptions that do not include channel interchange. Considering the omnichannel perspective is a new approach.

Overall, guests' booking expectations can be modified by tactical decisions, such as introducing booking without immediate charge, free cancellation, allocating a low number of rooms to one channel, immediate discounts, or deal of the day. These type of price-focused endogenous variables play important roles. Also, exogeneous variables, such as online reviews (Zhang et al., 2019) and online reputation (Yang et al., 2019) might affect tourists' expectations of price changes. However, number of channels or platforms might also add more complexity, as follows. Our current research interest is at both levels: type of channel and platforms within channels. At platform level, expectations might be influenced by the multiple booking sources (i.e. online platforms) that show up within a search. This is typically done by online aggregators (e.g. trivago) and comparative apps (e.g. rastreator.com) and the supplier level might include intermediaries and hotel websites. At channel-type level (e.g. OTAS versus hotel), tourists may have different expectations for pricing policies by channel based on their assumptions, knowledge, or previous experience. Indeed, while the cancellation rate is 17% for online booking, it is only 4% for travel agency bookings (Falk & Vieru, 2018). This evidence supports the taking of an omnichannel perspective toward the analysis of tourist behavior. To illustrate this increasingly complex scenario, a tourist might be aware of the best accommodation rates by channel, almost like an expert, or tech-savvy consumers may understand the workings of opaque pricing channels (e.g. Hotwire.com), bidding options in tourism (e.g. betterbidding.com) (for details, see Yang et al., 2019) and very last-minute deals (hoteltonight.com) (see Yang & Leung, 2018). The growing importance of this segment and their awareness in terms of anticipating price changes represent a complicated challenge for revenue management (Chen &

Schwartz, 2013).

From the customer's viewpoint, length of stay might influence room rates. However, the relationship between room rates and length of stay remained unexamined until recent times and needs closer attention (Riasi, Schwartz, Liu, & Li, 2017). Customers expect lower nightly room rates for longer stays (Schwartz, Riasi, & Liu, 2018). Consequently, it is interesting to analyze the potential influence of length of stay on hotel rates. Riasi et al. (2017) found empirical evidence of higher nightly room rates when guests stayed longer, although this varies depending on hotel rating. Furthermore, the gap between customer expectations and actual room rates has been seen to increase over the number of nights reserved (Schwartz et al., 2018).

2.4. Channel interchange

The omnichannel environment favors tourist channel interchange behaviors. This is boosted by low online information search costs. Each channel offers distinctive features which, in turn, create the circumstances where a single distribution channel will not dominate the hospitality market (Lei, Nicolau, & Wang, 2019; Yang & Leung, 2018). The influence of distribution channels on RevPAR has scarcely been considered (Lei et al., 2019), let alone in regard to advance booking.

Channel interchange is searching and booking across different channels and intermediaries (e.g. OTAs) versus direct channels (hotel websites). Interchange within intermediaries is searching and booking within type of channel, such as Booking.com and Hotels.com, to name only two. As discussed earlier, online aggregators typically offer prices from more than one intermediary which, in turn, makes it more valuable to research at channel level. In both these cases, previous consumer information search literature argues that consumers make trade-offs between the marginal utility of new information versus marginal search costs. A great deal of literature on optimization modeling addresses this search process (e.g. Branco, Sun, & Villas-Boas, 2012; Chen & Yao, 2016; Ke & Villas-Boas, 2019). In the intermediary interchange setting, the search cost is lower due to the online aggregators. However, in channel interchanges, search costs are not simple to estimate and might come from a sequential, or simultaneous, searching process (Honka & Chintagunta, 2016; Kim, Alburquerque & Bronnenberg, 2016). These valuable contributions assume a given price and overlook dynamic pricing. Basically, dynamic pricing "refers to the tactical practice of determining optimal room rates contingent upon the day and time when a reservation is received" (Yang & Leung, 2018, p. 199). In an omnichannel setting, this is of high interest for both guests and managers, in terms of getting the best price and maximizing revenues, respectively.

The hospitality literature shows inconclusive findings. Some studies show that local travel agencies offer the lowest rates for luxury hotels, but OTAs provide the best rates for mid-priced hotels. Surprisingly, research has found the most expensive prices on hotel websites. Other studies have found no significant differences between direct and indirect channels (for a review, see Yang & Leung, 2018) and no rate parity between hotel and OTA websites (Toh, Raven, & DeKay, 2011). These inconclusive findings might be attributed to the lack of hotel-related studies, as suggested by Abrate et al. (2012), but other factors might also explain price dispersion by channels, as Yang and Leung (2018) suggested. In this recent paper they found that the previous literature explains price disparity by channel, dependent on hotel type, star rating, and booking time.

Therefore, while our study zeros in on the effect of advance booking on hotel rates and the way channels influence that effect, we also attempt to control for hotel characteristics (star rating, size and location), seasonality, and length of stay. These factors will be parsed across different distribution channels in a multi-hotel setting.

2.5. Type of hotel

From the supply side, several dimensions influence hotel pricing, such as location (hotel type, urban vs resort), hotel size, hotel quality-hotel star rating, and seasonality (Wang & Nicolau, 2017).

The quality of a hotel affects its pricing policy. It seems reasonable to argue that higher-quality hotels are more reluctant to vary prices due to their lower sensitivity to demand and to maintain their reputations (Becerra, Santaló, & Silva, 2013; Lee, 2015). However, the empirical findings are conflicting. Lee, Tang, and Fong (2016) found that high-class hotels show greater price disparity than low-class hotels. Similarly, Yang et al. (2019) found similar results in the case of opaque discounts. Interestingly, Abrate et al. (2012) found a relationship between the low star rating urban hotels and price change. Their findings differed between working days and weekends. On working days, lower star category hotels decreased their prices more than high star rating hotels, but they increase them by more during the weekends. Despite these differences between working and weekend days, it seems that high-star hotels are able to maintain stable pricing policies over time based on their reputation and lower price sensitivity. Conversely, low-star hotels are more sensitive to price changes. As Lee (2015) concluded, the quality of the hotel is contingent upon similar type of competition in the same location.

Hotel size and, more specifically, the number of rooms available, is recognized as a key factor in defining dynamic pricing. This has been discussed as the total number of available rooms in the same location (Abrate et al., 2012). At hotel level, the argument for price dispersion might be that small hotels face higher fixed costs per room than larger resorts which, in turn, pushes them to vary prices to increase room occupancy rates.

Hotel location is a double-edged sword. On the one hand, locations with many hotels tend to respond to high demand while isolated hotels tend to respond to specific needs or be in unique locations. The first issue goes back to the discussion about the number of rooms available in a destination and the distance to the most attractive resources (Guizzardi et al., 2017, 2019). A closer analysis of location introduces the concept of differentiation. The hospitality literature shows that, for Mediterranean hotels, OTAs prefer uniform pricing over time (Melis & Piga, 2017) and Abrate and Viglia (2016) found less price variations over time, depending on number of competitors.

Seasonality also affects price dispersion. The literature shows that in the low season lower-scale hotels offer higher discounts, whereas higher-scale hotels tend to increase prices (Guizzardi et al., 2017). Quality is again the key explanatory factor for these lower price changes, as higher-scale hotels attempt to keep their high-quality image (Abrate et al., 2012). However, other factors, such as tourist type, play a role. Guizzardi et al. (2017) found that seasonality has less impact in the business market, since these travelers normally have little flexibility in their reservation dates.

3. Dataset

The data set consists of monthly information on 1085 hotels in several Spanish destinations, with 39,363 booking observations. IDISO (the main Spanish hotel distribution service provider) collected the data from January 2012 to March 2014. In addition to this being a rich database, the importance of the potential results is underlined in that Spain is one of the top three global destinations in terms of arrivals and the second in international tourism receipts, after the US (UNWTO, 2018).

The data collection was done automatically through Idiso. The longitudinal period of 27 consecutive months (January 2012–March 2014) coincides with a period of a great affluence of customers in an attempt to assure a sample that was large enough for our purposes. Accordingly, the variability of the sample—in hotel types as well as number of destinations—would allow us to play it safe in terms of representativeness of the

Spanish market, both in its urban and coastal destinations. Note that Idiso represents approximately 10% of the market (Hotel & Tourism, 2017).

The data set covers a rich and diverse range of Spanish accommodation: it covers chains and independent hotels, small and large facilities, urban and coastal locations, one-to-five star rated hotels, and non-seasonal areas (e.g. the Canary Islands). Although the data set covers chain and independent hotels, the anonymized final data set does not show this characteristic. The distinctive features of the data set are: (i) multiple destinations, both urban and non-urban; (ii) collected over 27 consecutive months; (iii) examining four booking channels, including hotel websites, OTAs, call centers and GDSs.

Table 1 shows the variables used in the study. The average daily room rate is just short of €90, and the average advance booking time (measured as the number of days from the reservation to the arrival day) is close to 28 days. In terms of distribution channel, OTAs (37.1%) and hotel web pages (27.5%) were the most used. Most of the hotels have between 101 and 600 rooms (62.9%), 4-stars (67.2%) and are in urban locations (65.7%).

Table 1
Descriptive statistics.

Variables (N = 39,323)	Mean	Standard deviation
Rate (€)	89.6	47.7
Advance booking (days)	27.7	37.8
Length of stay (nights)	3.05	2.39

Variables (N = 39,323)	Proportion
Hotel website	27.5
Call center	17.2
OTA	37.1
GDS[a]	18.2
Hotel size 1-25	2.5
Hotel size 26-100	32
Hotel size 101-200	33.4
Hotel size 201-600	29.5
Hotel size >600[a]	2.7
1 star[a]	0.3
2 stars	2.2
3 stars	23
4 stars	67.2
5 stars	7.2
Urban hotel	65.7
Beach hotel[a]	34.3
Year 2012	41.6
Year 2013	46.4
Year 2014[a]	11.9
Jan[a]	10.4
Feb	11.0
Mar	11.5
Apr	7.6
May	7.7
Jun	7.7
Jul	7.7
Aug	7.6
Sep	7.6
Oct	7.4
Nov	6.9
Dec	6.9
Canary Islands	3.9

[a] Baseline for the dummy variables.

4. Methodology

The effects of the variables "advance booking" and "channel type" on room rates are examined through regression analysis. The empirical model is as follows:

$$\ln(Rate_{itc}) = \alpha + \beta_1 \cdot AdvBook_{itc} + \sum_{c=1}^{C} \beta_{2c} \cdot Ch_{itc} + \sum_{c=1}^{C} \beta_{3c} \cdot Ch_{itc} \cdot AdvBook_{it} + \sum_{h=1}^{H} \beta_{4h} \cdot CV_{ith} + \varepsilon_{itc}$$

where $Rate_{itc}$ is the average rate per room for hotel i month t and channel c, α is the constant term, β_1 is the coefficient that captures the effect of the variable "advance booking" ($AdvBook_{itc}$), β_{2c} is associated with the effect of each channel type c (Ch_c) measured through dummy variables for hotel website, call center, OTA and GDS (baseline), β_{3g} reflects the effect of the interaction between "advance booking" and "channel type", β_{4h} is the coefficient associated with the *h-th* control variable CV_{hit} (size, number of stars, year, month, the different pattern of seasonality in the Canary Islands, and length of stay) and ε_{itc} is the error term, that follows a normal distribution.

We use the logarithm transformation of the dependent variable so the potential effect of outliers is diminished, and we were able to interpret the parameters in terms of semi-elasticities, that is, the percentage change of the dependent variable when the independent variable shifts by one unit.

Also important is the control for potential endogeneity, especially when dealing with the pricing strategy (Abrate et al., 2019) wherein multiple factors—known and unknown—may interact. It should be noted that the error term can be correlated with the variable "advance booking". On the one hand, rate and advance booking can be simultaneously affected by the same factors; if these factors are unknown by the researcher, endogeneity would be due to a case of omitted variables (Greene, 2012). In our context, an omitted variable would act as an "uncontrolled confounding variable" that explains the dependent variable "rate" and the independent variable "advance booking". As the variable is not known, its exclusion could bring about correlation between "advance booking" and the error term. On the other hand, both variables—rate and advance booking—can have an effect on each other simultaneously: advance booking can have an influence on the levels of prices set by revenue managers (e.g. booking curves determine hotel rates) and the levels of prices can incentivize or deter the demand at a specific time in advance of the arrival date, thus affecting how in advance customers make their reservations.

Endogeneity leads to biased parameter estimates, thus hypotheses testing can be misleading (Greene, 2012). Therefore, we need to control for this potential effect of endogeneity and a traditional method to solve this issue of endogeneity consists of estimating the models by resorting to two-stage least squares (2SLS); note that with the use of instrumental variables, this method entails using instruments that are not correlated with the error term but are correlated with the endogenous regressor (i.e. advance booking), so that endogeneity is controlled. In the first stage, the endogenous regressor is regressed on all exogenous variables plus the instruments (*InstrAdvBook*):

$$AdvBook_{itc} = \delta_0 + \delta_1 \cdot InstrAdvBook_{itc} + \sum_{c=1}^{C} \delta_{2c} \cdot Ch_{itc} + \sum_{c=1}^{C} \delta_{3c} \cdot Ch_{itc} \cdot InstrAdvBook_{it} + \sum_{h=1}^{H} \delta_{4h} \cdot CV_{hit} + \varepsilon_{itc}$$

with the δ parameters, we estimated the predictions of the endogenous regressor ($\widehat{AdvBook}_{it}$). Note that the goal of this first stage is to compute these predictions because they are uncorrelated with the error term. In the second stage, the dependent variable is regressed on all exogenous regressors and the predictions obtained in the previous stage.

$$\ln(Rate_{itc}) = \alpha + \beta_1 \cdot \widehat{AdvBook}_{itc} + \sum_{c=1}^{C} \beta_{2c} \cdot Ch_{itc} + \sum_{c=1}^{C} \beta_{3c} \cdot Ch_{itc} \widehat{AdvBook}_{it} + \sum_{h=1}^{H} \beta_{4h} \cdot CV_{ith} + \varepsilon_{itc}$$

A key issue in 2SLS is the selection of appropriate instrumental variables. Consequently, different instruments are empirically tested as discussed in the following section.

5. Results

We tested for heteroscedasticity, collinearity and endogeneity. The Breusch-Pagan test detects heteroscedasticity ($F = 45.46$; $p < 0.001$); thus, we employed White heteroscedasticity consistent standard errors to estimate the models. The test for potential collinearity found that the condition indexes were all below the recommended value of 30 (Neter, Wasserman, & Kutner, 1989). Finally, the Durbin-Wu-Hausman test confirmed the existence of endogeneity with the variable "advance booking" ($J = 179.30$; $p < 0.001$). Consequently, it is appropriate to use 2SLS with instrumental variables. To select appropriate instruments, we use variables that are not correlated with the error term ε_{itc} and that are correlated with the regressor "advance booking". Accordingly, we built and empirically tested six instruments that complied with these requirements: (i) average advance bookings per month; (ii) average advance bookings per month by removing the sample observation from the calculation; (iii) advance bookings obtained from averaging the same month but using years other than the year the observation was realized; (iv) average advance bookings for each month, controlling for the different seasonality of the Canary Islands; (v) average advance bookings for each month by removing the sample observation from the calculation and controlling for the different seasonality of the Canary Islands; and (vi) advance bookings obtained by averaging the same month but taking years other than the year of the observation and controlling for the different seasonality of the Canary Islands. According to the Cragg-Donald test, the optimal instruments are the first two variables, (i) and (ii), which were used for the 2SLS estimation.

Table 2 presents the results of the two-stage least squares analysis. In order to have a reference point for comparison, Model 1 shows the OLS estimates which do not control for endogeneity. When compared to Model 2, which does control for endogeneity, we observed that, in general, even though the explanatory powers of both models are similar, the size of the parameters of the main variables (advance booking, channels and the interactions between them) was smaller when endogeneity was taken into account. This reduction in size is explained by the fact that, if endogeneity is controlled, part of the variation of "advance booking" is expected to be captured by the exogenous variables, thereby attributing a smaller proportion of this variation in "advance booking" to the causal effect on the dependent variable "Rates".

As to the effects of the variables of interest, we found that advance booking, and the three channels, hotel website, OTAs and call centers -GDS is the baseline category-have significant, positive parameters, and their interactions (advance booking x channel type) have negative, significant impacts. While the positive parameter of advance booking suggests that the farther away from the arrival day, the higher the rates,[1] more important to our purposes is the negative differential parameters for each channel. To interpret these effects globally, we add the main effect of the channel and the interaction effects; accordingly, the vertical axis in Fig. 1 shows the joint impact of these main and interaction effects and the horizontal axis refers to the number of days before the arrival day (The graph shows the marginal effects of the variables mentioned in the caption). We can see that for bookings made 90 days in advance, GDSs offer better rates for the customer, followed by OTAS (although they are not so different from hotel websites) and call centers offer higher rates (as indicated, GDS is the baseline category, whose parameter takes value zero, it should be interpreted as if it were depicted as a flat line over the horizontal axis crossing the vertical axis at zero— Note that the constant is not considered in these figures as we graph the effects that vary as the number of days out changes). As time goes by, rates increase; in fact, one month in advance, hotel websites, OTAs and GDSs offer similar price levels, with GDSs listing the most competitive prices as the arrival day approaches.

As for the control variables, as expected, the higher the number of stars, the higher the rates; the smaller hotels tend to offer higher prices; and urban hotels have lower rates than resorts. As for the time-related variables, it is important to point out that the Canary Islands have a different pattern of seasonality to the other Spanish destinations. The parameters that capture these effects show significant effects on November, December and January. Finally, as for length of stay, the significant and positive parameter found means that longer stays relate with higher rates.

6. Discussion

Focusing first on the variables of interest (the three channels and their interactions), the global effect found shows that for bookings made 90 days in advance, GDSs offer better rates than the rest of the channels. Rates diminish steadily, and one month out, hotel websites and OTAs offer similar price levels. This dynamic pricing is in line with the finding of Abrate et al. (2012) and Yang and Leung (2018). It is interesting to note that despite the fact GDSs offer the best rates well in advance, people tend to book one month out (27.7 days to be precise—see Table 1). These results reveal that other variables, beyond price, might have an influence on consumer behavior in terms of advance booking. While saving money when booking well in advance may be enticing, it may sometimes come at a cost; for example, depending on a hotel's cancellation policy, the uncertainty of booking three months out makes the option of reimbursement appealing but the non-option of reimbursement rather deterrent.

These results also respond to the question whether there is any price dispersion in advance bookings by channel type. The patterns of the rates displayed by hotel websites and OTAs are relatively close to each other over the study period. This is not surprising because, unlike

[1] *Note that in the global Model 2, a parameter of 0.003 for advance booking is obtained. As a semi-log equation is used, this means that for every day an average 0.3% change in prices is expected. While 0.3% may be negligible for one day, when we take, say the average of 28 days, the variation in prices is 8.4%, which is substantial. Obviously, we do not expect a linear increase by 0.3% every day (the application of revenue management should not lead to a fixed pattern like this), however, on average, for a period of 28 days this variation in rates is not minor. When we include the interaction with each channel, this amount diminishes for hotel website, call center and OTA as their parameters are positive, bringing about a global effect of 2.8%, 5.9% and 2.8%, respectively.*

Table 2
The effect of "advance booking" and "channel type" on hotel rates.

Variables	Model 1		Model 2		Model 3		Model 4	
	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD
Main variables								
Advance booking	0.004[a]	0.0003	0.003[a]	0.0350	0.004[a]	0.0350	0.004[a]	0.0003
Hotel website	0.047[a]	0.0067	0.036[a]	0.0002	0.207[a]	0.0002	0.421[a]	0.0454
Call center	0.073[a]	0.0075	0.062[a]	0.0066	0.234[a]	0.0115	0.423[a]	0.0466
OTA	0.060[a]	0.0061	0.049[a]	0.0071	0.259[a]	0.0121	0.296[a]	0.0452
(Hotel website)*Advance booking	−0.002[a]	0.0003	−0.002[a]	0.0060	−0.003[a]	0.0115	−0.004[a]	0.0004
(Call center)*Advance booking	−0.002[a]	0.0003	−0.001[a]	0.0002	−0.002[a]	0.0002	−0.003[a]	0.0005
(OTA)*Advance booking	−0.003[a]	0.0003	−0.002[a]	0.0002	−0.003[a]	0.0002	−0.004[a]	0.0004
Control variables								
2 stars	0.358[a]	0.0304	0.360[a]	0.0338	0.338[a]	0.0334	0.333[a]	0.0309
3 stars	0.718[a]	0.0270	0.719[a]	0.0318	0.695[a]	0.0314	0.692[a]	0.0276
4 stars	0.999[a]	0.0271	1.000[a]	0.0318	0.975[a]	0.0314	0.969[a]	0.0277
5 stars	1.557[a]	0.0280	1.560[a]	0.0324	1.521[a]	0.0321	1.527[a]	0.0285
Hotel size 1-25	0.061[a]	0.0159	0.062[a]	0.0158	0.042[b]	0.0157	0.305[a]	0.0477
Hotel size 26-100	−0.138[a]	0.0113	−0.139[a]	0.0113	−0.143[a]	0.0112	0.069	0.0398
Hotel size 101-200	−0.155[a]	0.0111	−0.156[a]	0.0112	−0.159[a]	0.0111	0.019	0.0401
Hotel size 201-600	−0.107[a]	0.0109	−0.108[a]	0.0111	−0.111[a]	0.0109	−0.043	0.0403
Urban hotel	−0.147[a]	0.0059	−0.148[a]	0.0047	0.004	0.0093	−0.150[a]	0.0059
Year 2012	−0.037[a]	0.0064	−0.037[a]	0.0066	−0.033[a]	0.0065	−0.037[a]	0.0064
Year 2013	−0.036[a]	0.0064	−0.036[a]	0.0065	−0.034[a]	0.0064	−0.036[a]	0.0063
Feb*(1-Canary)	0.039[a]	0.0074	0.039[a]	0.0076	0.039[a]	0.0075	0.038[a]	0.0074
Mar*(1-Canary)	0.077[a]	0.0072	0.077[a]	0.0075	0.075[a]	0.0074	0.076[a]	0.0072
Apr*(1-Canary)	0.093[a]	0.0085	0.093[a]	0.0087	0.091[a]	0.0086	0.091[a]	0.0084
May*(1-Canary)	0.127[a]	0.0085	0.126[a]	0.0087	0.125[a]	0.0086	0.125[a]	0.0084
Jun*(1-Canary)	0.167[a]	0.0087	0.166[a]	0.0087	0.165[a]	0.0086	0.164[a]	0.0087
Jul*(1-Canary)	0.186[a]	0.0092	0.186[a]	0.0088	0.184[a]	0.0086	0.184[a]	0.0092
Aug*(1-Canary)	0.189[a]	0.0093	0.189[a]	0.0088	0.188[a]	0.0087	0.187[a]	0.0092
Sep*(1-Canary)	0.108[a]	0.0086	0.107[a]	0.0088	0.108[a]	0.0087	0.106[a]	0.0085
Oct*(1-Canary)	0.038[a]	0.0086	0.037[a]	0.0088	0.042[a]	0.0087	0.037[a]	0.0085
Nov*(1-Canary)	−0.01	0.0086	−0.011	0.0089	0.001	0.0088	−0.01	0.0086
Dec*(1-Canary)	−0.011	0.0088	−0.011	0.0089	−0.001	0.0088	−0.009	0.0087
Feb*Canary	0.035	0.0324	0.036	0.0366	0.037	0.0362	0.033	0.0316
Mar*Canary	0.016	0.0331	0.016	0.0362	0.013	0.0357	0.015	0.0325
Apr*Canary	−0.13[b]	0.0395	−0.13[b]	0.0415	−0.132[b]	0.0409	−0.134[a]	0.0386
May*Canary	−0.09[c]	0.0378	−0.09[c]	0.0421	−0.091[c]	0.0415	−0.09[c]	0.0367
Jun*Canary	−0.003	0.0389	−0.003	0.0416	−0.011	0.0411	−0.009	0.0376
Jul*Canary	0.058	0.0385	0.058	0.0417	0.050	0.0412	0.055	0.0369
Aug*Canary	0.047	0.0377	0.048	0.0419	0.038	0.0414	0.039	0.0367
Sep*Canary	−0.026	0.0378	−0.026	0.0413	−0.033	0.0407	−0.031	0.0368
Oct*Canary	0.03	0.0386	0.03	0.0416	0.023	0.0411	0.026	0.0380
Nov*Canary	0.039	0.0386	0.038	0.0413	0.038	0.0407	0.038	0.0378
Dec*Canary	0.048	0.0401	0.048	0.0417	0.045	0.0412	0.046	0.0389
Canary	0.07[b]	0.0236	0.068[c]	0.0269	0.067[c]	0.0266	0.073[b]	0.0232
Length of stay	0.016[a]	0.0020	0.017[a]	0.0011	0.014[a]	0.0011	0.016[a]	0.0019
Urban hotel, channel type and advance booking								
(Hotel website)*Urban hotel					−0.276[a]	0.0134		
(Call center)*Urban hotel					−0.274[a]	0.0147		
(OTA)*Urban hotel					−0.295[a]	0.0127		
(Hotel website)*Advance booking*Urban hotel					0.004[a]	0.0004		
(Call center)*Advance booking*Urban hotel					0.004[a]	0.0002		
(OTA)*Advance booking*Urban hotel					0.004[a]	0.0011		
Hotel size, channel type and advance booking								
(Hotel website)*Hotel size 1-25							−0.521[a]	0.0563
(Call center)*Hotel size 1-25							−0.365[a]	0.0615
(OTA)*Hotel size 1-25							−0.415[a]	0.0642
(Hotel website)*Advance booking*Hotel size 1-25							0.003[a]	0.0005
(Call center)*Advance booking*Hotel size 1-25							−0.001	0.0011
(OTA)*Advance booking*Hotel size 1-25							0.004[a]	0.0011
(Hotel website)*Hotel size 101-200							−0.404[a]	0.0462
(Call center)*Hotel size 101-200							−0.379[a]	0.0480
(OTA)*Hotel size 101-200							−0.239[a]	0.0459
(Hotel website)*Advance booking*Hotel size 101-200							0.003[a]	0.0004
(Call center)*Advance booking*Hotel size 101-200							0.003[a]	0.0005
(OTA)*Advance booking*Hotel size 101-200							0.001[a]	0.0004
(Hotel website)*Hotel size 201-600							−0.228[a]	0.0469
(Call center)*Hotel size 201-600							−0.220[a]	0.0483
(OTA)*Hotel size 201-600							−0.132[b]	0.0462
(Hotel website)*Advance booking*Hotel size 201-600							0.002[a]	0.0004
(Call center)*Advance booking*Hotel size 201-600							0.001[b]	0.0004
(OTA)*Advance booking*Hotel size 201-600							0.002[a]	0.0004
Constant	3.454[a]	0.0316	3.464[a]	0.0350	3.375[a]	0.0350	3.33[a]	0.0492
R-squared	0.394		0.393		0.409		0.402	
Adjusted R-squared	0.393		0.393		0.409		0.401	
F-statistic	607.55		602.03		562.62		396.32	

a = $p < 0.001$; b = $p < 0.01$; c = $p < 0.05$.

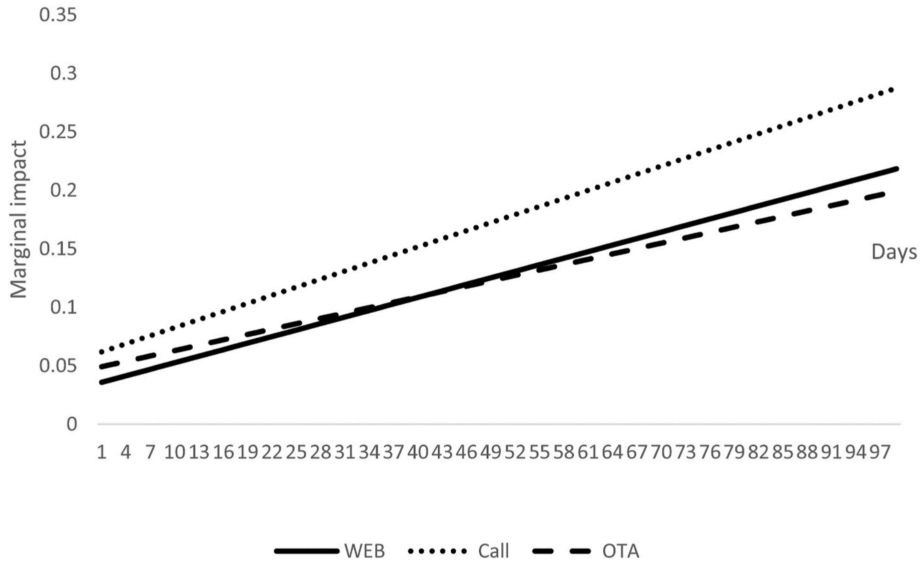

Fig. 1. Global effect of advance booking and channel type.

countries such as Germany, France, Italy, Austria, Belgium and Sweden that have banned rate parity clauses, these agreements have not been outlawed in Spain. So, if we look at the general patterns, the close relationship between the rates on hotel websites and OTAs is a consequence of this rate parity agreements. However, when a hotel's type and size are controlled, some larger discrepancies between both rates seem to emerge, thus the general results described before are nuanced when some hotel characteristics—type and size—are included.

Regarding the hotel type—urban vs resort—the finding that urban hotels have lower rates than resorts can be explained by the fact that the vacation character of the destinations led to higher average prices at resorts. Therefore, the hotel type is a determinant factor of rates, in line with Guizzardi et al. (2019). As for the hotel size, the result that the smaller hotels tend to be associated with higher rates can be due to the higher fixed costs per room they face. It means that hotel size and, in particular, the number of rooms available has an effect on dynamic pricing; which is in line with Abrate et al. (2102).

In an attempt to further discuss the effect of these two variables—hotel type and size—we estimate Models 3 and 4, which take into account the interactions of these variables with channel type and advance booking.

Model 3 shows the estimates for urban hotels. The results show a reverse effect in comparison to the global estimates in Model 2; in particular, the interactions of hotel type with channel type (hotel website, call center and OTA) showed negative, significant parameters in all cases, while the interactions with "advance booking" showed positive, significant effects. To determine which effect prevails, we aggregated, as before, the main and interaction effects (see Fig. 2). This shows us that, with urban hotels, closer to the arrival day prices are lower. This reduction is especially remarkable for call centers, which show a steeper

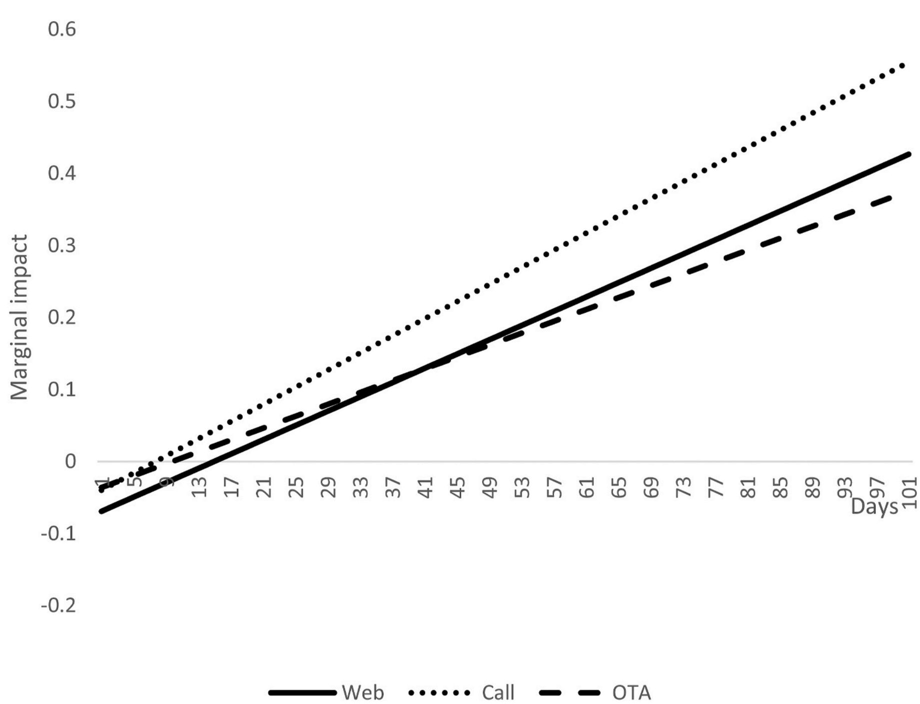

Fig. 2. Effect of advance booking and channel type by hotel type (cities).

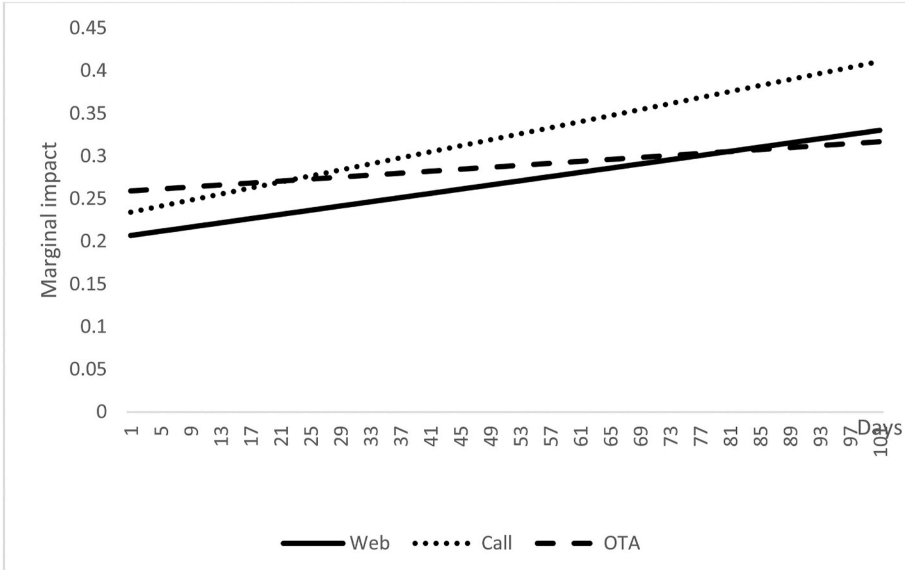

Fig. 3. Effect of advance booking and channel type by hotel type (resorts).

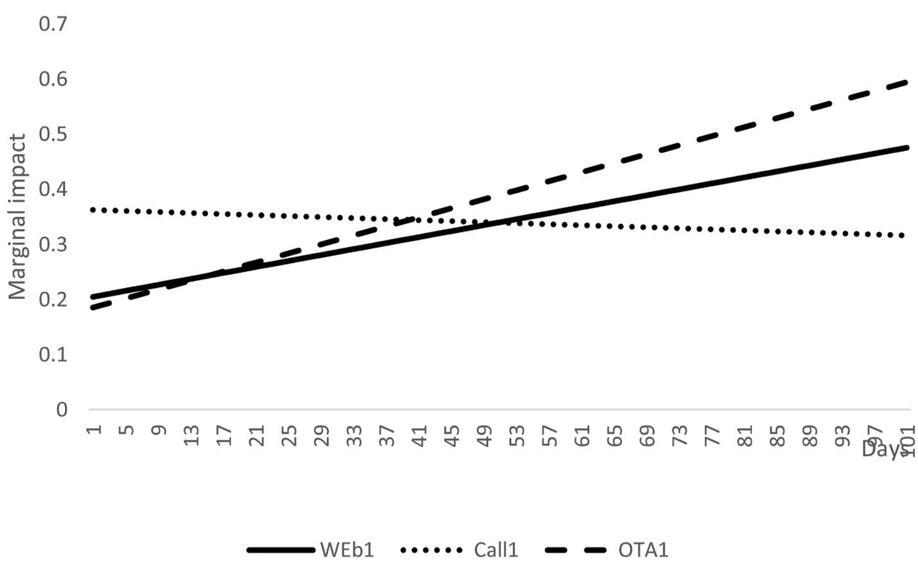

Fig. 4. Effect of advance booking and channel type by hotel size 1-25.

slope; this discount, while it exists, is less drastic for hotel websites and OTAs. For comparative purposes, we re-estimated the model with resorts (taking cities as the baseline). Fig. 3 shows these effects.

Model 4 presents the estimates for each hotel size and their interactions, where all but one parameter are significant. Specifically, we find that the interactions of hotel size with channel type have negative, significant parameters, while the interactions with advance booking have positive, significant effects. Nevertheless, when aggregating all these effects, it is important to emphasize the different patterns of impacts that emerge in each channel type (see Figs. 4–7).

Fig. 4 shows that, for the smallest hotels (between 1 and 25 rooms), in comparison to the baseline category (that is, hotels with more than 600 rooms), the GDS channel offers the most competitive prices, call centers raise rates -with a slightly steep slope-as the arrival day approaches, and that hotel websites and OTAS lower prices as check-in approaches. Fig. 5 presents the patterns for hotels with between 26 and 100 rooms. Hotel websites and call centers reduce rates as arrival day approaches. OTAs, contrary to the pattern with the smallest hotels, also tend to reduce prices with a steeper slope. Fig. 6 depicts the effects for hotels with between 101 and 200 rooms. All channels show decreased prices as arrival day approaches, in a similar fashion to the previous graphs. Fig. 7 shows the impacts for hotels between 201 and 600 rooms. It is the only case where hotel websites, OTAs and call centers present parallel lines in the effects on rates. In fact, while the GDS channel has the lowest prices within two months of arrival, OTAs hold their prices lower than hotel websites; it seems that these hotels rely heavily on OTAs to fill their rooms.

Concerning the time-related variables, the fact that the parameters associated with the months of November, December and January are significant indicates, first, that the Canary Islands have a different pattern of seasonality compared to the other Spanish destinations, and second, while being located in the Canary Islands has a positive and significant effect on rates all year round, compared to the other Spanish destinations, the prices in the Canary Islands are lower just after Easter (April and May); however, the off-season in the rest of the country is in November, December and January. Obviously, these different patterns between the Canary Islands and the rest of Spain can be also influenced by the eminently tourist character of the Canary Islands, in line with

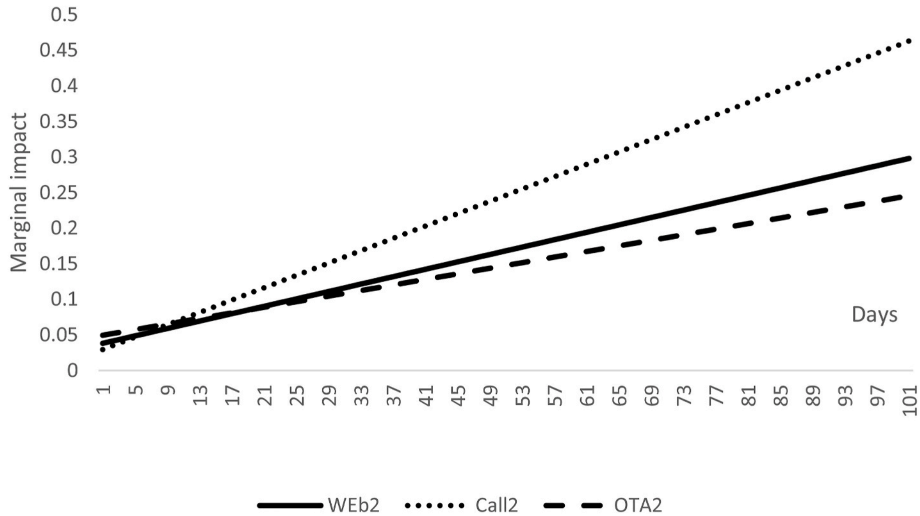

Fig. 5. Effect of advance booking and channel type by hotel size 26-100.

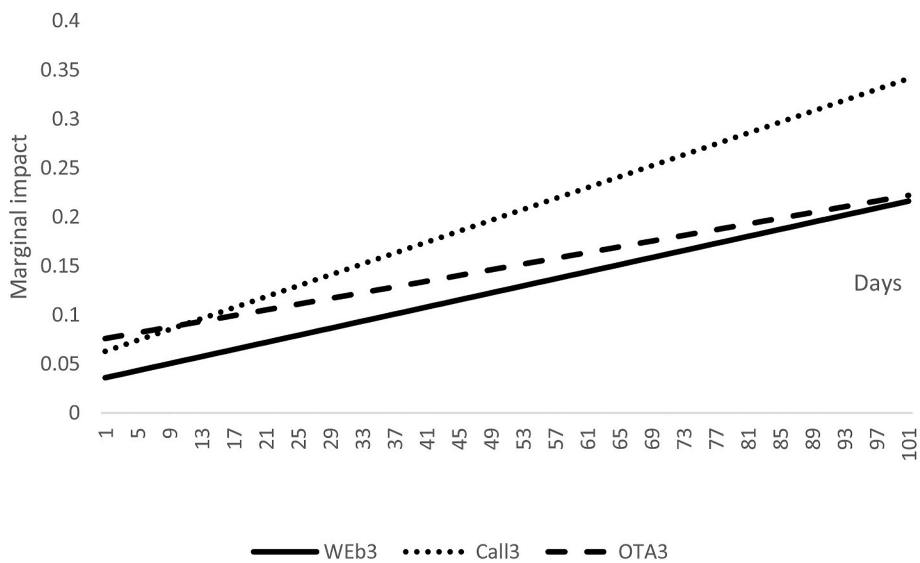

Fig. 6. Effect of advance booking and channel type by hotel size 101-200.

Guizzardi et al. (2017).

Finally, as for the significant and positive parameter of length of stay, it suggests that longer stays relate with higher rates, in line with the results of Riasi et al. (2017), which are based on the supply and production cost literature that argues that guests who stay longer are less price sensitive.

7. Conclusions

This research has analyzed the effects of advance booking and channel type on room rates using a sample of 1085 hotels with 39,363 observations. The application of 2SLS has allowed us to control for potential endogeneity and arrive at the following conclusions and implications sorted by channel, hotel characteristics (location and hotel size), and behavioral aspects (length of stay).

Beyond the empirical outcome that the farther away from the arrival day, the higher the rates, a first substantive result is the finding that there are differential effects when channels are considered. Ninety days in advance, GDSs undercut any other channel's price, which reflects their attempt to capture bookings in advance by offering lower fees than the other channels. Although OTAs show lower rates than hotels ninety days out, thirty days out, the rates offered by hotel websites and OTAs align. This suggests either a competitive reaction of hotels to close the price gap or a proactive initiative of OTAs for increasing their margin. We might suspect that such OTAs incremental fee tactic is driven by previously accomplishing the booking goals set up for the 60 and 90 days in advance of booking. A closer analysis by hotel type (urban vs resort) reveals idiosyncratic impacts. In particular, for urban hotels, as check-in day gets closer, rates go down with a much steeper slope. When the channels were introduced into the model, it was observed that hotel websites had their lowest price level on the arrival day, while call centers showed a drastic reduction over the period of three months prior to arrival.

Focusing on hotel size, it appears to have an influence on the general effects of advance booking and channel type. When hotel size is included, diverse impacts arise: i) for the smallest hotels (between 1 and 25 rooms), the GDS channel offers the most competitive prices and, as arrival day gets closer, call centers raise their rates, whereas hotel websites and OTAs lower their rates; ii) for hotels with between 26 and 100 rooms, as check-in day approaches, hotel websites, call centers and OTAs lower their rates; iii) hotels between 101 and 200 rooms display a common decrease in rates on hotel websites, OTAs and call centers as the

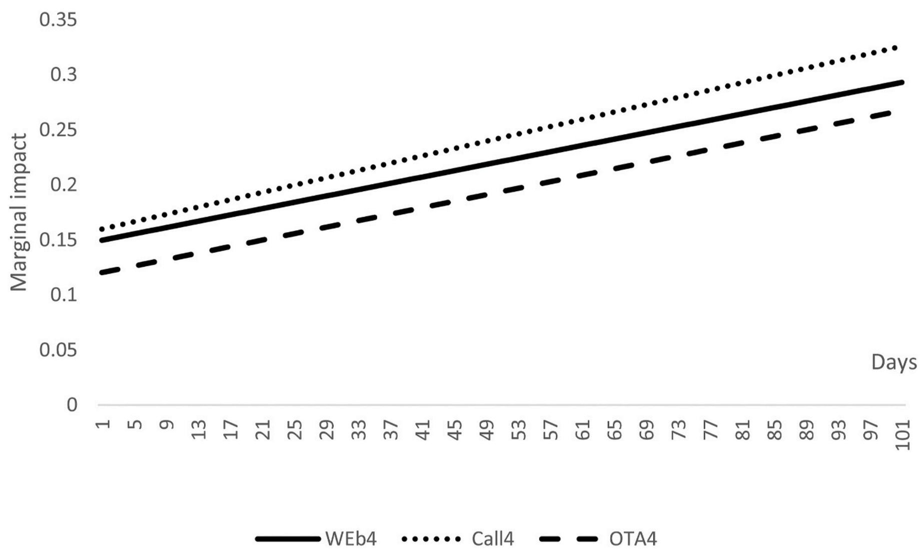

Fig. 7. Effect of advance booking and channel type by hotel size 201-600.

arrival day nears; and iv) hotels between 201 and 600 rooms show a similar pattern as the previous size, but with a notable difference: while for the hotels with between 101 and 200 rooms, hotel websites rates were below OTA rates at all times, for hotels with between 201 and 600 rooms, OTAs consistently undercut the rate on hotel websites. The behavioral aspect analyzed (length of stay) also reveals some differences in booking rates. Length of stay explains rates with a positive relationship: the longer the stay, the higher the rate.

While advance booking and pricing have been studied in the literature by following different approaches, such as surveys, experiments, or modelling (Zhang et al., 2019), analyses *using multiple types of channels*—intermediaries (i.e. online travel agencies) and direct channels (i.e. hotel websites)—and using *real data* from *multiple destinations*, are scarce (Zhang et al., 2019). Consequently, a first contribution of this study to the literature is that it analyzes the effect of advance booking on hotel rates *across four channels* (hotel websites, OTAs, call centers and GDSs), using *real data* collected over 27 consecutive months from *multiple Spanish destinations*. With managers steadily adopting dynamic pricing—wherein digital transparency of prices is a key issue—the current multi-channel setting needs further research that permits a certain level of generalizability regarding advance booking and accommodation prices. Accordingly, our multi-destination approach used allows us to better generalize the results and the use of more than one year of data permits controlling for seasonality. Apart from this comprehensive theoretical contribution, looking at some specifics, we first stand out that trying to unearth a general effect of advance booking on rates can be misleading; this is not only due to the application of dynamic pricing but because different hotel characteristics, such as type and size, lead to distinct pricing strategies; and second, when endogeneity is controlled, the size of the advance booking parameter is smaller. Therefore, controlling for potential endogeneity when analyzing the relationship between advance booking and room rate is fundamental.

As for the managerial implications, the study's findings can guide hotel managers in their pricing strategies over time by hotel type (e.g. size, quality and location), and by channel. Considering that dynamic pricing is gaining momentum due to the increasing complexity of combining pricing policies over time in a dynamic scenario, the results obtained can shed some light on some facets of a hotel's revenue management strategy as follows. First, in the current multichannel scenario, hotel managers must be aware of the fact that consumers can learn the underlying pricing strategies of hotels by channel; thus, "knowing what they know" can be a critical input for a hotel's decision-maker. More specifically, as the results showed that channel management is effectively conducted based on advance booking - as the basic principles of revenue management indicate, the patterns found by examining each channel should help managers in their pricing tactics, as they can see which channels should be used, and how long in advance. Also, while call centers consistently present the highest prices, the exception observed for the smallest hotels might be an indication that greater efficiency can be achieved.

Second, since advance booking rates differ by size of hotels and channels, it is important to note that tourists should look at the channel but also consider the size of the hotel. This insight affects both, small and large hotels, when setting their room rates by channel. Third, our study reveals that the quality of the hotel (i.e. number of stars) is positively correlated with rates. Fourth, from a destination perspective, urban and resort hotels have different pricing dynamics. Interestingly, OTAs tend to maintain stable prices for urban hotels, which again might suggest the potential use of more efficient dynamic pricing strategies implemented by hotels when they sell their rooms directly to the customer. Fifth, the finding that OTAs offering the best rate 90 days in advance and people booking one month out is relevant in terms of managerial implications because it means that other variables different from price have an impact on consumer behavior in terms of advance booking. It seems that some consumers face a trade-off: saving money if booking *well* in advance and the uncertainty of booking *too much* in advance as many events may happen between the booking day and the arrival day. Therefore, hotel managers can design a strategy (via cancellation policy and the reimbursement policy thereof) to entice consumers to book at a specific time.

This study has some limitations deriving from the dataset. First, hotel occupancy is not included, and therefore a critical factor in pricing decisions is not considered. Second, although the number of competitors is implicitly considered because of the high number of hotels analyzed, hotel density by destination and channel is not explicitly addressed. Third, the fact that we are using monthly average prices may hide some effects bringing about counterintuitive relationships such as the effect of length of stay; also, along this line, as we do not have information on the hotel's daily rates or the room categories sold, we are not able to incorporate the hotel's differentiation strategy into the model. Fourth, the different cancellation rates per channel have not been considered and may exert an influence on booking decisions.

Finally, as to future research avenues, it is notable that, while the analysis of rate parity was not an objective of the research, we observed some patterns that might be worthy of examination. In the analysis of the general effect (Fig. 1), the small *dis*parity between the rates offered by OTAs and hotel websites can be explained by the rate parity agreements signed by OTAs and hotels. However, when controlling for hotel type, there is more disparity (Fig. 2), and when hotel size is introduced, we found anomalies, such as the existence of different strategies based on hotel size: hotel websites undercut the rates of OTAs for hotels with between 101 and 200 rooms and consistently beat the rates of hotel websites for hotels with between 201 and 600 rooms. Further research must extend advance booking focus on peer-to-peer accommodation (Gibbs, Guttentag, Greztzel, Yao & Morton, 2018), less competitive accommodation providers such as campgrounds, and tourism hedonic services such as cruises (Espinet, Fluviá, Riagli). Also, future research should address the growing influence of smart phones when booking (Sun, Law & Schukert, 2020). Further, it can be complemented with an in-depth analysis with an omnichannel approach based on device attribution. Also, research might explore whether the place of origin of the travel—whether domestic or international—might affect advance bookings. Finally, although the lack of data on cancellation policies applied by hotels does not allow us to include this dimension in our analysis, its inclusion if future analyses would permit the examination of hotels' efficiency when it comes to implementing dynamic pricing.

Credit author statement

Enrique Bigne has developed the theoretical framework, discussion, and overall review. Juan Luis Nicolau has contributed to this paper by defining the empirical strategy and doing all the estimations. He has also contributed to the discussion. Edu William has developed the initial idea and the discussion. Also, he got the data set and cleaned it.

Impact statement

Dynamic pricing is gaining momentum due to the increasing complexity of combining pricing policies over time in a dynamic scenario. The results of this study should help revenue managers increase their effectiveness when using multiple channels and designing tactics related with advance booking (e.g. by allocating a greater number of rooms to some channels). Also, from a destination perspective, urban and resort hotels have different pricing dynamics, and interestingly, OTAs tend to maintain stable prices for urban hotels, which suggests the potential use of more efficient dynamic pricing strategies implemented by hotels. Importantly, we find that other variables different from price have an impact on consumer behavior in terms of advance booking. The trade-off between "saving money if booking *well* in advance" and "the uncertainty of booking *too much* in advance" is central, making cancellation policies critical to entice consumers to book at a specific time.

Declaration of competing interest

None.

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