Are all online hotel prices created dynamic? An empirical assessment

Melis, Giuseppe and Piga, Claudio A

Department of Economics and Business, University of Cagliari,
Keele Management School, Keele University

1 December 2016

Are all online hotel prices created dynamic? An empirical assessment.

Giuseppe Melis
Department of Economics and Business
University of Cagliari
Viale Sant'Ignazio, 09123 Cagliari (Italy).
gemelis@unica.it

Claudio A. Piga* *(corresponding author)*
Keele Management School,
Keele University
Keele, Staffordshire, ST5 5BG (United Kingdom)
c.piga@keele.ac.uk

Abstract:

Understanding how tourist firms set their online prices is important due to their growing reliance on Online Travel Agencies (OTA). Little is known, however, about whether differences exist in the online pricing approaches adopted by hotels using an OTA. The article tests, using a big data approach, whether the diffuse narrative of a pervasive presence of dynamic pricing provides a realistic description of hotels' pricing behavior and thus challenges the view that dynamic pricing should be considered the prevailing norm for the industry. The evidence suggests a heterogenous attitude across hotels, with uniform pricing being more widespread in most hotels of our sample, namely, the 3-star or less, while dynamic pricing is more likely applied in higher quality hotels.

Keywords: *Revenue Management; Online travel agents; Heterogeneous strategic management behaviour; dynamic pricing.*

Acknowledgements

We are extremely grateful to Marco Alderighi, Alberto Gaggero and Marcello Mariani for their helpful comments and suggestions. The usual disclaimer applies. Piga gratefully acknowledges receipt of the Visiting Scientist scholarship offered by the Sardinian Regional Government, L.R.7/07.

1. Introduction

Despite the enormous importance of such Online Travel Agents (OTAs) as Booking.com or Expedia as a key distribution channel for many hospitality firms, very little is known about the way such firms set and manage their prices on the OTAs platforms. From a technological viewpoint, a platform enhances price transparency and lowers menu costs, i.e., the cost incurred by a firm when it modifies its price, thereby contributing to the creation of a frictionless market, as originally hypothesized in Bryniolfsson and Smith (2000). From an economic perspective, companies that use OTAs as distribution channels must set their prices in a context where competition is intensified on both the supply side (more firms against which to compete) and on the demand side, with consumers better informed and potentially capable to choose among alternative destinations located afar from each other (Andrés-Martínez et al., 2014: 172).

Prima facie, both perspectives implicitly call for a somewhat sophisticated pricing approach capable of allowing a firm to adapt to the varying market conditions that prevail on the platform. Indeed, as Noone and Mattila (2009: 272) observe "... the growth of the Internet as a channel of distribution has significantly increased customer exposure to revenue management pricing practices". This works aims to better qualify such a statement by investigating whether the propensity to apply such techniques is widespread in the universe of firms, or is instead largely heterogeneous and thus can be related to specific firms and market attributes (Dolnicar and Ring, 2014).

So far, the academic literature has mostly focused on the theoretical reasons why the adoption of Revenue Management (RM) pricing techniques manifest itself in price variation over time (McAfee and te Velde, 2007; Talluri and van Ryzin, 2004). The empirical studies based on the airline industry robustly support the notion of an intense intertemporal dynamism in the fares set by both low-cost carriers (Alderighi *et al.,* 2015) and full-service carriers (Bilotkach *et al.*, 2010; Borenstein and Rose, 1994; Gerardi and Shapiro, 2009). In hotel markets, intertemporal pricing also appears to be an important empirical regularity, although little attention has been given to whether it characterizes the price setting behavior of all the firms in the sample (Abrate *et al.*, 2012; Fleischer, 2012). An exception in the literature is Abrate and Viglia (2016), whose approach, which explicitly controls for the presence of heterogeneous behavior in the use of intertemporal pricing across hotel operators, is in line with the findings from a survey carried out by the Global Business

Travel Association (GBTA) in 2014, where it emerged that although 75% of the respondents declared to be aware of the possibility to use Dynamic Pricing (DP) to manage their hotel rates, only 22% made active use of it (GBTA, 2014).

This article's main contribution to the travel and tourism literature consists in shedding empirical light on the heterogenous intertemporal pricing behaviour of hospitality firms operating on an OTA. It tests whether the use of an online platform is, as predicted by the literature and the media, accompanied by an intensive RM approach revealed by a frequent change in the posted price of a hotel room. To this purpose, data were collected using a special software programmed to issue queries on the online platform of Booking.com (Abrate and Viglia, 2016; Fleischer, 2012). The queries were for the duration of one night in hotels based in many seaside localities of the four main Mediterranean islands of Sardinia, Sicily, Corsica, and the Balearics. The sample covers days of stay during the period from 1st April to 30th September, which is much longer than the one adopted in existing studies and thus enables a comparison across different parts of the seaside holiday season; it also covers two consecutive years (2014 and 2015). The data refer to double rooms in hotels with a star classification, whose prices are tracked at regular intervals prior to each date of stay, thus allowing us to study the evolution of posted prices over a 70-days period, denoted as "booking period", and the extent by which each establishment engages in dynamic changes of its offered prices.

The empirical analysis aims at developing a set of stylised facts characterising the temporal pricing profile adopted by a wide variety of hotels. Such facts arise as a direct answer to the following research questions:

1. How widespread is the adoption of DP strategies among the hotels that use an online platform?
2. Are there differences in the use of these strategies, in relation to such factors as the type of structure (e.g., its star classification), the area in which it is located, the number of days separating the query from the "day of stay", the customers' ratings and the period of stay during the season?
3. Conditional on observing a price change during two consecutive dates in the booking period, which of the above factors are more strongly associated with the probability that the change corresponds to a price increment?

To anticipate results, we find no evidence in our data in support of the view that the majority of hotels are constantly reprogramming their yields by frequently adjusting their

rooms' prices. Furthermore, our empirical analysis strongly indicates an heterogenous, and previously unreported, propensity towards online DP across the firms in the sample. Star classification appears to be the strongest discriminant factor, with higher quality hotels (i.e., 4 and 5 star) always showing to be the most active in terms of DP, regardless of the way in which we measure it. Symmetrically, lower quality hotels (3 star or less), which make up the great bulk of enterprises in the data, exhibit a low propensity to vary prices over time, despite the reduced "frictions" made available by the OTA's platform in terms of low menu costs and easier observability of competitors' prices. Although our data collection is similar to that in Abrate and Viglia (2016), we cover different periods and geographical areas, and reach a rather different conclusion, in so far as their findings suggest more price dynamism, i.e., a larger coefficient of variation, in lower quality firms. Furthermore, another contribution of this study is to suggest the presence of countervailing factors preventing or hindering the widespread adoption of intense DP techniques, such as for instance, the fear that DP may be perceived as unfair by customers (Choi and Mattila, 2004; Heo and Lee, 2011; Orbach and Einav, 2007).

As far as the second research question is concerned, in addition to the star classification, another factor that appear to play a role in explaining the heterogeneous propensity to vary prices over time is the period during the season. In both years, a much larger proportion of price variations is observed during the period from July to September; moreover, holding the period fixed, more variations took place in 2015 than in 2014. Interestingly, firms with similar characteristics exhibit a similar pricing behaviour across the four regions, an indication that the propensity to vary prices inter-temporally is robustly associated with the factors used in the empirical analysis.

Finally, the third research question investigates more closely whether the price variation corresponds to an increase or a decrease. At an early stage of the booking period, the probability that a price change corresponds to a price increase is above fifty percent for most types of star classifications (i.e., price increases dominate over decreases), but such a percentage declines as the end of the booking period approaches. That is, in all macro-destinations, during the three weeks preceding the day of stay the probability of a price drop dominates, in line with the common belief that last-minute discounts are offered by hotels to improve their load factors (Mauri, 2012).

2. Literature review and main research questions

Revenue Management (henceforth, RM) refers to a broad set of price-setting techniques that are profitably used by such companies as airlines, hotels, car retails, cruise shipping, etc. In such industries customers are heterogeneous, i.e., they have different willingness to pay and may learn at different point in time whether they need to buy the service; demand is uncertain, in the sense that peak demand may occur unexpectedly; the service is highly perishable (Kimes, 1989). In its simplest formulation, RM entails a trade-off between accepting now a booking request at a given price or refusing it leaving the unsold capacity available tomorrow for a potential customer willing to pay a higher price (McGill and van Ryzin, 1999).

The existing literature on RM has highlighted a set of major drivers that are expected to enhance or hinder price variation over time in travel and tourism markets (see for example Balaguer and Pernias, 2013; Chen and Schwartz, 2008). We will consider them in the two subsequent subsections. In the whole Section, unless otherwise specified, we will refer to "firms" to indicate both airlines and hotels, the types of enterprises on which the literature on RM has mostly focussed.

2.1 Factors expected to be positively associated with dynamic pricing.

Intertemporal price variation can be revealed by either upward or downward adjustments in the current price. The factors driving prices in either directions are often correlated with time, that is, the temporal distance that separates the date the service was booked from the date of consuming it (i.e., the travel date for airlines or the date of stay for hotel). We first consider those factors that are expected to lead to price increases, and then discuss the factors expected to drive prices in the opposite direction.

First, because consumers may be heterogeneous along such relevant dimensions as their willingness to pay for the service or the uncertainty on whether they need to travel, firms may want to try to segment the market and price discriminate the business travellers' segment from other lower demand travellers, e.g., those travelling for leisure or for visiting friends and family. Indeed, business travellers, in comparison to the other group, can generally afford to pay a higher premium. The temporal effect is induced by the fact that business people are more likely to discover whether they need to travel only a few days before the consumption date and their choice of travelling dates is therefore very inflexible; in such circumstances, it should be expected that the prices of flights and hotel rooms

increase a few days before the day of travel. (Alderighi et. al. 2016; Gaggero and Piga, 2011; Gale and Holmes, 1993).

Second, firms may respond to the online presence of strategic customers, i.e., those who may postpone the purchase in anticipation of last-minute discounts, by committing to raise prices over time to discourage such behaviour (Li et al., 2014). Such a strategy is still compatible with price reductions, as long as these occur randomly and do not disrupt the overall increasing temporal trend of prices (Deneckere and Peck, 2012; Sweeting, 2012).

Thirdly, and most importantly, an important aspect of RM in airline markets is denoted as "inventory control". It consists in setting *i*) ticket classes, i.e., fare levels and associated restrictions (refundability, advance purchase, business vs. economy, etc.) and *ii*) defining the number of seats available at each fare. The equivalent in hotel markets would be, assuming identical room characteristics, deciding *i)* the relevant booking classes and *ii*) the number of rooms to sell in each class. Dana (1999) demonstrates, using advanced mathematical techniques within a model where all units of capacity (airlines seats or hotel rooms) are homogenous, that it is optimal for firms to divide their capacity into "buckets", each characterised by a varying number of seats or rooms and by a monotonically increasing price level. The units in a bucket are all sold at the same price, and once they sell out, the price moves automatically upwards to the next bucket's price level. Alderighi et al. (2015) test the implications of Dana's model for the case of the airline industry; they find that an increasing intertemporal fare profile is strongly driven by the increasing scarcity of available seats, that is, the fare goes up as the plane fills up. Dana (1999) assumes price discrimination away, and the monotonically increasing price profile that arises in equilibrium is ascribable to differences in the shadow cost of each unit of capacity; therefore, the findings in Alderighi et al. (2015), further extended in Alderighi et al. (2016) suggest that having information on the load factor of an aircraft or hotel at the time a price is posted, is necessary to disentangle an intertemporal price discrimination motive from cost-based pricing. In this work, we do not have information of the number of rooms available in the hotel at the time a price was posted; this is not a limitation, because both intertemporal price discrimination and cost-based pricing related to inventory control are expected to operate in the same direction to produce a variation in room prices, which is the focus of our empirical strategy.

Abrate *et al.* (2012) study whether the temporal structure of hotel prices depends on the composition of customers' type, defined by the motivation of stay. They argue that on weekdays the hotels serve a larger proportion of business customers, while on weekends

hotels serve predominantly leisure ones. Based on the price of a single room posted online between three months and one day before the stay by about 1000 hotels in eight European capitals, the evidence reveals that over 90% of prices changed during the period, and that the intertemporal price profile varies depending mainly on the mix of customers the hotels anticipate they will be serving.

Prices may be dropped for two main theoretical reasons. One, hotels and airlines offer a highly perishable product. Because an unsold seat or room carries no value for the firm, during the booking period, there is a strong incentive to lower prices, which are therefore expected to fall over time (McAfee and teVelde, 2007; Talluri and van Ryzin, 2004). Two, a price reduction is the simplest and most straightforward method used by firms to stimulate a sluggish demand. To reduce learning effects that enhance strategic behaviour by consumers, the literature has revealed that European low-cost airlines offer secret discounts (Bachis and Piga, 2011) or generally apply price reductions randomly to reduce their predictability. Bilotkach et al. (2014) find that such price drops are effective in enhancing an airline's load factor (see also Salanti, Malighetti and Redondi, 2012).

2.2 Reasons favoring uniform pricing.

There are both cost-based and strategic reasons why firms may choose a uniform pricing approach. Zbaracki et al. (2004) show that, for the case of industrial products and services, managerial and customer costs to change prices are relevant. They identify three components of managerial costs: those related to the time and attention required of managers to gather the information, those pertaining to the resources to make the decision and, finally, the communication costs to the different members of the firm, to explain the logic of the change. Additionally, other costs include those incurred to prepare customers to the price changes. They estimate that managerial costs are more than 6 times, and customer costs are more than 20 times, the simple cost of changing nominal prices, the so called "menu costs" (Bryniolfsson and Smith, 2000).

As far as the strategic reasons favoring a uniform pricing approach are concerned, perceived (un)fairness, uninformed customers and demand uncertainty are often cited factors (Orbach and Einav, 2007).

The (un)fairness of a price is a very controversial issue along a number of dimensions but above all because the perception of fairness or unfairness of a price is always a matter of judgment that depends on multiple factors such as the context of past purchases,

product knowledge and brand communication strategies both formal (advertising) and informal (word of mouth, online reviews). This also means that the decision to purchase is not only based on the price quoted by the company, but the comparison between it and the singular customer's idea of the current price (Kotler et al., 2015). In the travel and tourism industry, the high variability of prices over time constitutes an intrinsic aspect of RM and can therefore be perceived as "unfair" by consumers who have paid a higher price than other customers. In tourism, the perception of price equity/iniquity plays an important role in customer satisfaction and subsequent behavior (Oliver and Swan 1989). If hotel clients perceive RM practices as unfair, the increase in revenues resulting from such practices may be only short-term since it can lead to a decrease in customer satisfaction and, ultimately, to the reduction of their loyalty (Kahneman, Knetsch, and Thaler 1986; Kimes 2002). This is particularly important for online markets due to the growing reliance of customers on reviews and ratings issued by past customers (Mathies et. al, 2013; Leung et al., 2013)

Because tourism and hotel services are typical examples of “experience goods” (Nelson, 1970), i.e., goods whose quality can only be properly assessed after consumption, customers could perceive the price as a quality signal; in such a case, any price drop below the uniform price could lead to a sharp decrease in demand. Such an effect may play a relevant role during the booking period for sale on a specific date of stay: if the hotel managers drops its price during the booking period, the potential customers may think something is less than ideal in either the hotel or the destination, and be deterred from buying (Orbach and Einav, 2007).

Demand uncertainty may, on the other hand, explain why the same price is applied to all the days of stay within a given season period: indeed, hotel managers may be unable to predict the demand for specific dates, arguably because their prospective appeal is unknown. In such a case, firms may decide to treat all dates of stay in a period (say, August or June) identically (Orbach and Einav, 2007).

The above discussion has highlighted drivers of both price change and uniformity; given their contrasting effects, we posit our:

Research Question 1: How widespread is the adoption of DP strategies among the hotels that operate online?

2.3 The importance of the organizational design and other characteristics.

Hospitality establishments differ in their degree of organizational complexity, which in turn may impact on the way they design and implement their pricing schemes. In the hotel industry, Selmi and Dornier (2011) emphasize the role of the human factor in the establishment and development of an effective RM system. Their qualitative analysis based on interviews to both general and specific revenue managers highlights a number of relevant points. First, both types of managers must work together to determine the hotel's strategy. One of the interviewees in Selmi and Dornier (2011) report that: "the job of yield [or revenue] manager in a hotel is very important ... in some hotels the yield manager is as important as the hotel manager (p. 66)". Second, RM personnel must be properly trained but an understanding of RM concepts is also a requisite for hotel managers. Third, the IT infrastructure constitutes an invaluable source of information but it does not take away a revenue manager's autonomy of decision. Overall, the foregoing discussion suggests that the pricing scheme which a hotel applies, is the final outcome of a complex interaction between an organization's characteristics, its culture and the processes linking the operations of the various functions (marketing, RM, etc). Because all such aspects are generally unknown and unobserved by the researcher, it is not possible to establish a direct causation between the way an organization is, broadly speaking, managed, and the pricing scheme it adopts. However, organizational complexity is highly positively correlated with such observable characteristics as the star classification or the establishment's capacity, which we adopt in this study to address our:

Research Question 2a: How is the propensity to engage in DP correlated with a hotel's star category and size?

In a study of hotels that operate under the same chain name (which may therefore have shared organizational practices), Kosová et al. (2013) report no significant differences in performance between franchised and company-owned hotels. Similarly, Hung, Shang and Wang (2010) find that the price in chain affiliated hotels in Taiwan does not differ significantly from those in independently owned ones, thus suggesting that geographically localized effects play an important role.

The analysis in Fleischer (2012), which like the present study reports data extracted from the Booking.com website for many Mediterranean localities, focuses on whether the hotels charge higher prices for a room with a sea view, after controlling for such other

possible price shifters as type of room, inclusion of breakfast and/or half board, non-refundability and other types of view (garden, city, etc.). The findings, which are based on only two specific days of stay, indicate a statistically significant "price premium" just above 10% in both days, and no significant variation of such a premium across the sampled Mediterranean areas.

Abrate and Viglia (2016) find empirical support to the hypothesis of a positive impact of online customer's ratings on prices. Their empirical model also includes the booking time, i.e., the time interval separating the date of stay from the date a price is posted online. There is, at least to our knowledge, no study that looks at the relationships between customers' ratings or the booking time and a firms' propensity to engage in DP, within a sample that also includes multiple spatial contexts and contiguous dates of stay across a full tourist season. We therefore extend the Research Question 2a to include geographical, reputational and seasonality factors:

Research Question 2b: How is the propensity to engage in DP correlated with the area in which a hotel is located, the number of days separating the room booking from the "day of stay", the customers' ratings and the period of stay during the season?

It is worth stressing that the focus on correlation is due to the impossibility to establish causation effects in our research design. The straightforward implication is that while we cannot state that any of the factors mentioned in Research Question 2a and 2b, "determines" a firm's propensity towards DP, we can evaluate the extent to which such a propensity co-moves with those factors.

3. Data Collection

The empirical investigation is based on primary data of online prices and other establishments' information retrieved using an "electronic web-crawler", a programme designed to connect directly to the website of one of the largest OTA in the world, Booking.com. The crawler was designed to automatically launch the online queries necessary to book an accommodation in a specific locality, and subsequently retrieve the posted prices together with information on the characteristics of the rooms offered and the establishment's name and rating resulting from the past customers' evaluation. Separately, the programme also retrieved other establishment's characteristics, including its type, its size measured by the number of rooms, if it is part of a chain and its star classification. In this work, to simplify the comparisons and provide a more direct link with the existing

literature, the analysis uses data only from establishments classified as Hotels, if they state a star classification on their Booking.com website. Furthermore, the study includes only double or twin rooms.

The queries specified the most important and famous tourist seaside localities located in four renowned regions in the western part of the Mediterranean Sea, denoted as macro-destinations: the French island of Corsica, the Spanish Balearics Islands, and the Italian islands of Sardinia and Sicily (see the Appendix for a list of the localities). Large seaside cities, such as the regional capitals of Cagliari in Sardinia, Palermo in Sicily and Palma de Mallorca in the Balearics, were excluded from the sample because their hotels, unlike in smaller seaside tourist localities, face a more heterogeneous type of demand including both tourists and business travellers, something which may induce a different pricing approach.

The period covered in our sample runs from 1st April until the 30th September. These denote the days of stay, which, for analytical purposes, were further divided into three sub-periods: April-June, July-August, and September. The first and the third correspond to periods of medium demand, while the second one identifies the peak-season in many seaside resorts. The data collection was repeated in two consecutive years, 2014 and 2015.

Similar to the approach followed in many airline studies (Alderighi et. al., 2015; Bachis and Piga, 2011; Bilotkach et al., 2010), the web crawler operated daily and was programmed to issue queries specifying dates of stay which differed from the query date by a specific set of time intervals. For a "hotel/day of stay" combination, the crawler requested prices 70, 65, 60, 55, 50, 45, 40, 35 30, 25, 20, 14, 7, 4 and 1 day prior to the date of stay, which henceforth we denote as the booking time. It is noteworthy that, for a given date of stay, booking time and consequently prices may not have been collected for the whole booking period if an establishment reached full capacity utilization early in the booking period (or decided to stop posting prices on Booking.com on specific dates of stay). So only combinations of "hotel/day of stay" with at least 5 prices retrieved on different booking times, were considered in the statistical and econometric analysis. All prices were retrieved in British Sterling (GBP).

Table 1 provides the number of hotels in each macro-destination, broken down by period of stay and class classification. In all macro-destinations, *i*) the number of hotels in each star classification remains quite stable across period; *ii*) at least seventy percent of hotels are classified as either 3- or 4-star, a proportion that reaches ninety percent in

Sardinia; *iii*) in Sardinia and Sicily, the incidence of 5-star hotels is about seven percent, slightly higher than in Corsica and Balearics (slightly less than five percent), where, however, we record a larger presence of 1- and 2-star hotels.

Table 2 clearly shows that, holding the star classification fixed, prices vary across the season in both years, with higher prices for stays in July-August, followed by those in September and in April-June. It is noteworthy that in this work, seasonal adjustments of price are not considered as evidence of DP, which we identify only in terms of price variations across the booking times, holding the date of stay fixed. Within each period of stay and macro-destinations, the retrieved prices are ranked, as expected, in line with the star classification.

4. Descriptive evidence

Some preliminary answers to both research questions, based on descriptive statistics, can be found in Table 3, which reports the likelihood of a price variation (either an increase or a decrease) between two consecutive booking times, holding the date of stay fixed. The row "Total" reports values in each macro-destination, broken down by period of stay: it therefore sheds some light on the extent by which DP is widespread in each geographical area. Despite the maximum five days' distance between booking times, the proportions of observations with a variation is generally below twenty percent in all periods, with a peak of about twenty-five percent in July-August 2015; it is always the lowest in the April-June period in both years, although there appears to have been more price dynamism in 2015. Overall, the evidence suggests that less than one hotels in five, in every macro-destination, changed its online room prices during two consecutive sample observations of the booking times.

To address the second research question, Table 3 reports the same likelihood broken down by star classification, and highlights important differences between types of hotels. In all periods, those classified as 3-star or less exhibit a much smaller propensity to change their online prices; the likelihood of a price variation in such establishments is less than fifteen percent, except for Corsica in July-September 2015 where, however, it does not reach the twenty percent threshold. Notably, even for higher quality hotels in 2014 the propensity to vary price dynamically hardly exceeds the thirty percent value; it increases in 2015, especially for 5-star hotels in Sardinia and Corsica during the July-August period, where it surpasses the fifty percent level. For 4-star hotels the likelihood of a price change, even in

2015, tends to stay around the thirty percent value, with only a peak of about forty-four percent in Corsica in July-September 2015. To sum up, the evidence in Table 3 indicates a generally low propensity to engage in DP in all macro-destinations, when all hotels are considered as an aggregate. However, the analysis based on the star classification points toward an heterogeneous propensity to change room prices dynamically, which is larger for 4- and 5-star hotels. Although this is an interesting insight, before we can conclude that the star classification is positively correlated with hotels' propensity to engage in DP, it is also necessary to control, using a multivariate analysis, for other factors that may be also correlated with the classification. For instance, if higher quality hotels have larger capacity, then the descriptive analysis based on star classification captures effects that pertain to hotel size.

Before doing so, we investigate the possibility that price variations occur asymmetrically during the booking times' period. As the literature review has highlighted, the three weeks preceding the date of stay define a period where, on the one hand, the hotels may want to seize the opportunity to price discriminate late bookers, but, on the other, may also face the risk of leaving rooms empty and thus be tempted to offer "last-minute" discounts. To allow comparisons with Table 3, Table 4, which reports the same likelihood values but broken down by different booking times, only considers price variations and does not distinguish between price decreases and increases; such a distinction will be investigated in Section 7. In 2014, there appears to be no clear-cut difference, in each period of stay, across booking times, except for the early period of 45-70, which indeed exhibits lower incidence values in both years. In all macro-destinations and across all the stay periods in 2015, the probability to observe a price change increases as the booking times decrease (i.e., as the stay approaches. However even in the July-August 2015 stay period, which records the largest incidence of price variation, our data indicate that no more than four hotels out of ten tend to change their prices in the four days that precede the stay.

To sum up, the descriptive statistical analysis suggests three main aspects with regards to the incidence of DP in our data: *a*) in all macro-destinations and a two years' period, only a small proportion of hotels appears to vary their prices at each point in time; in this sense, DP over the booking times' period appears to be on average a rather sporadic phenomenon; *b*) there seems to be some heterogeneity among hotels, with some, possibly higher quality hotels, actively involved in managing their prices over the booking period, while others choosing to maintain their prices fixed; *c*) the intensity with which price

variations are observed appears to be stronger during the last days of the booking period. All these factors will be simultaneously assessed in the following econometric analysis.

5. Econometric methodology

An advantage of using multivariate models arise from the possibility to evaluate and control for the impact of other factors that would not be feasible to include in the descriptive Tables of the previous Section. Another advantage comes from the possibility to estimate the effect of one factor in non-linear models in situations where each factor can be interacted with other variables.

In the previous Section, a DP treatment is identified by a dummy variable equal to 1 whenever we observe a change in a room's price over two consecutive booking times. That is, $Y_2^{jt} = 1$ if $\left|P_t^j \quad P_{t-1}^j\right| > 0$, where j denotes a "hotel/room type/date of stay" combination, and $\left|P_t^j \quad P_{t-1}^j\right|$ is the absolute difference of prices in two consecutive booking times t. Such a specification for the treatment variable Y_2^{jt} is useful for the investigation of when, during the booking period, the hotels are more likely to engage in DP.

However, the descriptive analysis in the previous section has highlighted that the probability that this may happen is indeed rather small at each point in time, although this does not rule out the possibility that all or most "hotel/room type/date of stay" combinations receive a DP treatment at least once during the booking period. If this were the case, then this would imply that most hotels manage the dates of stay dynamically, even if the treatment occurs sporadically over the booking period. The following treatment variable identifies this possibility: $Y_1^j = 1$ if $\sum_t Y_2^{jt} > 0$. The main difference between the two treatments is that Y_1^j is independent of the booking time and can be estimated by considering a smaller sample which includes only one observation for each "hotel/room type/date of stay" combination.

Both treatment variables are binary and are therefore estimated using a probit model (Wooldridge 2002): $P\left(Y_n^j = 1 \middle| \boldsymbol{X}\right) = G(\boldsymbol{X\beta})$, where $P\left(Y_n^j = 1 \middle| \boldsymbol{X}\right)$ denotes the probability that the treatment is administered, given a set of contributing factors $\boldsymbol{X}$ and G is the standard normal cumulative distribution function, which we will use to calculate the estimated probabilities after the coefficients $\boldsymbol{\beta}$ are estimated. The set of factors **X** include: a dummy for each macro-destination, interacted separately with the customers' Ratings, with the six periods of stay (April-June, July-August and September) in each year and also with three

dummies identifying Small, Medium and Large size hotels; a dummy for each star classification, interacted with the booking times' dummies only in the regression using Y_2^{jt} as treatment; a dummy for each Town where the hotels are located. The hotel size dummies were constructed using the threshold of twenty-five room to denote Small hotels; Large hotel have more than seventy rooms, while Medium hotels have between twenty-six and seventy rooms.

The use of many categorical factors aims at generating pre-defined clusters within which we calculate the probability to observe a DP treatment. For instance, although the previous section has indicated a smaller probability of the treatment Y_2^{jt} in, say, 3-star hotels, it might be possible that after controlling for such factors as Ratings or hotel size, we might be able to find no difference between 3-star and higher class hotels.

It is noteworthy that the variable Ratings may be simultaneously determined with our dependent variables, an aspect which prevents an interpretation of the econometric estimates in terms of causality but that does not prevent one in terms of correlation with the treatment (Wooldridge 2002). Indeed, on the one hand, the price discrimination due to a strong price variations is likely to affect an establishment's rating negatively, and may thus act as a deterrent to price fluctuations (Xia *et al*. 2004; Bolton *et al*. 2003); on the other, if a firm's competitive advantage arises from a high service quality, or if price fluctuations are perceived to be an industry's common practice, then a firm can freely adjust its prices dynamically without fearing to attract criticism from its customers (Mathies, Gudergan, Wang 2013; Ferguson 2014). In both cases, the hotel management may act in ways which we do not observe but that may target both the hotel's online pricing approach and its need to maintain or improve its customers' rating. Bearing this in mind, it is also likely that the simultaneity bias induced by the Ratings variable is rather negligible: indeed, the value of Ratings in each establishment is largely invariant over the sample period. It is thus generally pre-determined when the hotel managers make their observed DP decisions.

We choose nonetheless to discuss the impact of each factor in terms of their correlation with the treatment because some of the factors, such as star classification, size or location, cannot, by themselves, be associated with a causality effect. For instance, 4 or 5-star hotels and/or Large hotels are more likely to employ both a more complex organizational design and higher quality human capital; both unobserved factors are likely to be ultimately responsible for the observed price dynamism. Star classification and/or size

may well operate as their proxy, and profitably be used to investigate the second research question of whether different clusters exhibit a stronger than average propensity to DP.

6. Results

Because the estimation of both types of treatment includes a high number of interacted factors, reporting the list of all their coefficients would be uninformative, difficult to read and space consuming. Furthermore, probit models involve a non-linear estimation process, resulting in estimates that do not have a direct clear interpretation in terms of the factor's impact on observing the treatment, a problem which is exacerbated by the need to omit several base categories to avoid the dummy trap. To address all these issues, all results are reported only in graphical form, which are obtained as follows. We first run the probit models as specified in the previous section. Then, using the command "Margin" in Stata, we calculate the predicted probability, based on the probit estimated coefficients, of observing the DP treatment in clusters created by considering one fixed (i.e., the macro-destination), and two variable factors, for instance, the star classification and the hotel capacity. The estimated probabilities are then reported on a graph, to provide a clear image of differences between clusters.

6.1 Treatment independent of the booking time

Figures 1 to 3 report the estimated probability of Y_1^j, that is, the predicted proportion of dates of stay in which a hotel, defined by certain values of the factors, changed its prices during the booking period at least once. The two variable factors in Figure 1 are the star classification and the Rating, whose variation is measured by considering three values: 7, 8 and 9 (i.e., Low, Medium, High). The reported values suggest a direct answer to the first and the second research questions. Indeed, in all macro-destinations, it appears clear that 4- and 5-star hotels exhibit a stronger propensity to vary their prices dynamically. To explain how to interpret the graphed values, consider Corsica, where clearly Rating has no distinguishing impact. The model estimates that out of 100 dates of stay, 5-star hotels have on average, applied the DP treatment in about 80 days; the proportion falls to 70 for 4-star hotels, it is about 50 for 3-star hotels, and slightly above 30 for 2-star ones. In the Balearics, the model predicts similar values for 5-, and 3-star hotels, a higher value just below 40 percent for the 2-star category, a lower proportion of 60 percent for the 4-star one and also an estimate of about 30 percent in 1-star hotels. Sardinia and Sicily confirm the previous

finding of a divide for high quality hotels, but also exhibit a rather small difference in terms of Ratings within each star category. The model's prediction indicates a mild tendency for highly rated establishments to adopt DP more frequently, holding the star classification fixed (Phillips et. al, 2016). Such a difference is not, however, statistically significant, as estimates from the Margin command reveal (these are not reported to save space).

Figure 2, where Rating is replaced by the three categories of hotel size, also confirms the previous finding that the propensity to engage in DP tend to increase with the star classification, while size, like Rating, does not seem to be a correlated factor.

In the previous Figures, the predicted probabilities reported a composite effect across the different stay periods in our sample. Figure 3 investigates whether hotels in the same star category (and macro-destination) are more or less likely to apply DP in different periods of the season, and in different years. In all macro-destinations, the lines for the April-June stay periods in both years lie below all the other lines, that is, the proportion of days in this period with $Y_1^j = 1$ is the lowest within each star category. For example, in Sardinia's 2-star hotels, only about 30 percent of stay days in April-June receive the treatment, but this proportion increases to about 50 percent in all the other periods. A similar distinction can be made for all the star categories and is consistently found in all macro-destinations.

To sum up, the probability that DP is applied at least once during the booking period varies extensively and it is particularly low for 1- and 2-star hotels in all periods, and possibly for some 3-star hotels during the low-peak period of April-June. The estimates confirm the low probability of observing the treatment for many hotels in the sample; in terms of the Research question 1, this implies that DP is not very widespread across the universe of hotels using the Booking.com platform and that such hotels show at least an equal, if not stronger, propensity towards uniform pricing. Hotel size and Rating do not appear to be correlated with DP. As far as the Research Question 2 is concerned, the star classification appears to be the factor that best correlates with the probability to observe the treatment of DP. While the macro-destinations do not seem to be characterized by any visible difference, the hotels during the high peak periods in the Summer season show a greater propensity to adjust their prices dynamically.

6.2 The treatment varies with the booking time

Relative to Y_1^j, the investigation of Y_2^j should yield insights both on when, during the booking period, price variations are more likely to occur across clusters. Figure 4 reports, on the horizontal axis, the booking times, while each line corresponds to a star category. The values in the Figure complement well those reported in Table 4, which do not differentiate for the star category; once this is added, it appears clear that high quality hotels, and 5-star ones in particular, tend to have a higher than average propensity to vary their prices dynamically well ahead of the date of stay. Indeed, the probability to observe a price variation between two consecutive booking times is much higher in 5- and 4-star hotels: in these clusters, it fluctuates between 20 and 30 percent for 4-star hotels, and between 40 and 50 percent for 5-star ones. In all other categories, it hardly reaches values above 10 percent. Quite interestingly, over the last three weeks before the stay, the difference between categories tends to reduce drastically, due mostly to a strong drop in the propensity of high quality hotels to vary their prices, but also partly to an increase in the same propensity by lower quality hotels.

Figure 5 shows, in every sub-period, a growing probability of observing a price variation between two consecutive booking time which is due to a composite effect of the two opposing trends in Figure 4. The higher probabilities just a few days before the date of stay capture the larger weight of 3-star or less hotels, which are more numerous in every macro-destination. More importantly, the analysis of Y_2^j confirms the previous finding that DP is applied with a different intensity across different periods of the Summer season, with the lowest probability of observing the treatment reported in April-June. However, Figure 5 also indicates that, at least in Sardinia and Corsica, higher values characterize the 2015 sub-periods of July-August and September than in the corresponding periods of the previous year. Such values are also higher in the other two macro-destinations, but less evidently. Anecdotal evidence reported on the local press, and also gathered by one of the authors from discussions with Sardinian hoteliers, suggest that in 2105, as a consequence of the terrorist attacks in North Africa in 2014, many European seaside destinations enjoyed a boom in demand. Combined with the previous finding that the April-June sub-period always exhibit less DP, the analysis of Figure 5 overall suggests a positive relationship between the level of demand and the propensity to engage in DP. Overall, the use of a second treatment measure confirms the robustness of the previous findings and the answers to the Research

Questions: DP is prevalent only in higher quality hotels, which however are less numerous in every locality. Therefore, our work suggests that although DP is a relevant phenomenon in the hotel industry, its application is on average rather sporadic, with many firms choosing its mirror image, i.e., uniform pricing. Thus, our findings are consistent with the survey results published in GBTA (2014).

So far, the analysis has considered DP in terms of price variation (both increases and decreases). As Figure 5 indicates, the probability of observing such a variation is generally on average below 35 percent (except for Corsica in July-August 2015), although previous findings indicate a higher propensity for high-quality hotels. In the next section, we focus on whether similar conclusions could be drawn from the analysis where we distinguish between increases and decreases.

7. Price increases and decreases

To gain further insight and test previous findings' robustness, in this section we consider a third type of treatment:

$Y_3^{jt} = 1$ if $P_{t-1}^j \quad P_t^j > 0$ conditional on $\left|P_t^j \quad P_{t-1}^j\right| > 0$. That is, we only consider the observations in which we record a variation between two consecutive booking times, and flag those corresponding to a price increase. We can then perform an econometric analysis like the one of the previous section, calculate the probability of observing a price increase within different clusters and thus address:

Research Question 3. Conditional on a price variation taking place, which factors are more correlated with the probability to observe a price increase?

Figure 6 reports the predicted probability that a price variation corresponds to an increase, broken down by star category and booking times. In all macro-destinations, but especially in Sardinia, Sicily and the Balearics islands, between 65 and 30 days prior to the date of stay the increases make up the majority of price variation in all star categories. During the last 25 days of the booking periods, the incidence of price increases reduces, and therefore that of decreases becomes predominant, especially within the clusters including the 3- and 2-star hotels in Sardinia, Sicily and Corsica. Notably, in Corsica and the Balearics, the decreases dominate in all star categories during the last two weeks of the booking period, although the estimated probabilities differ in the two areas. In Corsica, only about 30 (70) percent of variations correspond to an increase (decrease), a value that drops to 20 (80) in the case of 2-star hotels. In the Balearics, decreases dominate with a 60 percent value which

does not differ across star categories. In Sardinia and Sicily, a similar finding appears to hold only for 3- and 2-star hotels, while higher quality hotels record a 50-50 chance to post either a decrease or a decrease, when they decide to vary their prices over the last two weeks of the booking period. Overall, Figure 6 provides some support to the notion that prices posted in the final part of the booking period are the result of two conflicting forces. On the one hand, the perishable nature of hotel rooms tends to drive prices down; on the other, if prices were consistently dropped within two weeks of the stay date, potential buyers would soon learn to postpone their purchases, thereby exacerbating the need for hotels to lower the price. As suggested in Li et al. (2014), hotels should therefore commit to an increasing price profile. Indeed, whenever a price variation is observed, such a variation is more likely to be an increase during the early part of the booking period (i.e., at least until 30 days before the stay date). Furthermore, although the proportion of decreases dominate in the final part of the booking period, these are overall not very likely to be observed. For instance, consider the Balearics in Figure 6, where on average 60 percent of variations in the last 14 days of the booking period are decreases. As previous findings in Table 4 and Figure 5 indicate, the probability of observing a variation during the same period is about 20 percent on average; therefore, the probability of a price decrease hinges, roughly speaking, around the 12 percent value, corresponding to one hotel in eight dropping its room price.

Figure 7 jointly considers how the probability of observing a price increase (decrease) *i*) varies during the season; *ii*) is affected by a positive exogenous demand shock like the one all macro-destinations experienced in 2015; *iii*) varies across the booking times. Interestingly, for all the 2015 periods in all macro-destinations, the probability to observe an increase follows a very similar pattern across the booking times: it stays above 50 percent everywhere but Corsica, where it drops around 40 percent in the last 14 days of the booking horizon. Previously, we suggested that a lower demand characterized the 2014 season relative to that in 2015; notably, the model predicts a lower incidence of price increases for the three 2014 sub-periods in Corsica; in the other macro-regions, one or two 2014 sub-periods report the lowest incidence of price increases for all the booking times. Thus, price decreases appear to be more likely applied when the hotel needs to revitalize aggregate demand; in such cases, decreases make up the greatest proportion of price variations even at an early stage of the booking period. Because decreases are also more likely during the last 14 days of the booking period, i.e., when the hotel managers have a clear understanding

of the realized demand, the estimates also confirm the "last-minute discounts" role normally assigned to price decreases, i.e., that of boosting a hotel's load factor on particular dates.

To sum up, the analysis aimed at providing an answer to Question 3 indicates that the probability to observe a price increase whenever a DP is applied: *i*) is lower for hotels of the 3-star category or lower, especially in the last three weeks of the booking period; *ii*) was lower in 2014.

8. Discussion and concluding remarks

The statistical analysis was designed to derive a set of stylized facts capable to suggest an answer to three research questions highlighted in the Introduction and in the Literature review section.

The answer to the first question distinguishes between two different types of treatments. In one case, we focus on whether at least one instance of price variation is observed during the booking period preceding the day of stay. We find that the answer to this question crucially depends on the hotel's star classification. For instance, for higher quality hotels (i.e., 4 and 5 star) on average about 60-80 percent of the days appear to be treated, i.e., they varied the price of a room at least once over the booking period. However, for lower quality hotels (3 star or less), the proportion falls well below 40 percent. In the other case, we investigate the probability that a price variation is observed between two sequential days in the booking period; for example, whether the price for a double room offered 40 days before the stay is different from the one posted 35 days before. The evidence is strongly in favour of a rather static pricing approach by hotels classified as 4 star or less: for such establishments, which make up the great bulk of enterprises in the data, the probability to observe a price change over two sequential booking days ahead of the stay is less than 30 percent. The findings in both cases thus reveal a low propensity to vary prices over time, despite the reduced "frictions" made available by the OTA's platform in terms of low menu costs and easier observability of competitors' prices. Although our approach is thus in line with that in Abrate and Viglia (2016), their findings suggest more price dynamism in lower quality firms.

As far as the second research question is concerned, the statistical analysis reveals that hotels tend to apply DP differently across the Season periods: for instance, uniform pricing, i.e., the mirror image of DP, tends to prevail in the low-peak months of April-June, but it is less likely found during the last part of the booking period.

The star classification does not appear to be a strong discriminant factor in the prediction of a price increase, whose likelihood is lower during the last days preceding the date of stay and in off-peak months during the Summer seasons.

The overall analysis suggests a set of managerial implications. First, the absence of online, and therefore easily visible, price variation for many firms may indicate a willingness to signal to potential competitors their intention to relax price competition by sticking to a set price (Gan and Hernandez, 2013). While this may be a viable strategy if the firm can achieve high enough occupancy rates, it could become a problem if the price stickiness leads to the reduction in arrivals at the destination level. Second, because active dynamic RM is more likely observed for firms that are vertically differentiated (that is, the 4- and 5-star hotels), those that are not may need to be incentivized by the Destination Management Organization (DMO) to seek marketing strategies aimed at revamping their products and expanding the set of ancillary services they offer. The investigation of the link between RM and the overall marketing mix adopted by a firm is left to future, possibly qualitative, research.

REFERENCES

Abrate, G., Fraquelli, G., and Viglia, G. (2012). "Dynamic pricing strategies: Evidence from Europea hotels". *International Journal of Hospitality Management*, 31(1): 160-168.

Abrate, G., and Viglia, G. (2016). "Strategic and tactical price decisions in hotel revenue management.", *Tourism Management*, 55: 123--132.

Alderighi M, Nicolini M, Piga CA. (2015). "Combined effects of load factors and booking time on fares: Insights from the yield management of a low-cost airline". *The Review of Economics and Statistics*, 97(4): 900-915.

Alderighi M, Nicolini M, Piga CA. (2016). "Targeting leisure and business passengers with unsegmented pricing". *Tourism Management*, 54: 502-512.

Andrés-Martínez, M. E., Gómez-Borja, M. Á., and Mondéjar-Jiménez, J. A. (2014). "A model to evaluate the effects of price fairness perception in online hotel booking". *Electronic Commerce Research*, 14(2): 171-187.

Bachis, E., Piga, C.A. (2011). "Low-cost airlines and online price dispersion". *International Journal of Industrial Organization*, 26(6): 655-667.

Balaguer J., Pernias J.C. (2013). "Relationship between spatial agglomeration and hotel prices. Evidence from business and tourism consumers". *Tourism Management*, 36:391-400.

Bilotkach, V., Gaggero, A., and Piga, C.A. (2014). "Airline Pricing under Different Market Conditions: evidence from European Low Cost Carriers". *Tourism Management*, 47:152-163.

Bilotkach, V., Gorodnichenko, Y. and Talavera O. (2010). Are airlines' price-setting strategies different *Journal of Air Transport Management*, 2010,1-6, 16

Bolton L. E., Warlop L., and Alba J.W. (2003). "Consumer Perceptions of Price (Un)Fairness.", *Journal of Consumer Research* 29:474-491.

Borenstein, S. and N. Rose (1994) "Competition and Price Dispersion in the U.S. Airline Industry", *Journal of Political Economy*, 102(4): 653-683.

Brynjolfsson, E. and Smith, MD. (2000). "Frictionless Commerce? A comparison of Internet and conventional retailers", *Management Science*, 46(4):563—58As Figure 5

Chen, C. C., & Schwartz, Z. (2008). "Timing matters: Travellers' advanced-booking expectations and decisions". *Journal of Travel Research*, 47(1), 35-42.

Choi, S., Mattila, A.S. (2004). "Hotel revenue management and its impact on customers' perceptions of fairness." *Journal of Revenue and Pricing Management*, 2(4): 303-314.

Dana Jr, J. D. (1999). "Equilibrium price dispersion under demand uncertainty: the roles of costly capacity and market structure". *Rand Journal of Economics*, 30(3), 632-660.

Deneckere, R. and J. Peck (2012) "Dynamic Competition with Random Demand and Costless Search: A Theory of Price Posting". *Econometrica*, 80(3):1185-1247.

Dolnicar S., Ring A. (2014). "Tourism marketing research: Past, present and future". *Annals of Tourism Research*, 47:31-47.

Ferguson JL. (2014). "Implementing price increases in turbulent economies: Pricing approaches for reducing perceptions of price unfairness". *Journal of Business Research*, 67(1): 2732-2737.

Fleischer A. (2012). "A room with a view—A valuation of the Mediterranean Sea view." *Tourism Management*, 33(3): 598-602.

Gaggero, A. and Piga, C. A. (2011) "Airline Market Power and Intertemporal Price Dispersion". *Journal of Industrial Economics*, 59(4): 552-577.

Gale, I. and Holmes, T. (1993). "Advance-Purchase Discounts and Monopoly Allocation of Capacity". *American Economic Review*, 83: 135-146.

Gan, L., Hernandez M.A. (2013). "Making friends with your neighbors? Agglomeration and tacit collusion in the lodging industry". *Review of Economics and Statistics*, 95(3): 1002-1017.

GBTA (2014). *Dynamic Hotel Pricing – Has its Time come?*, available at http://www.gbta.org/pressreleases/pages/rls_100114.aspx

Gerardi, K. and Shapiro, A. (2009). "Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry", *Journal of Political Economy*, 1-37, 117.

Heo C.Y., Lee S. (2011). "Influences of consumer characteristics on fairness perceptions of revenue management pricing in the hotel industry." *International Journal of Hospitality Management*, 30:243–251.

Hung, W. T., Shang, J. K., and Wang, F. C. (2010). "Pricing determinants in the hotel industry: Quantile regression analysis". *International Journal of Hospitality Management*, 29(3): 378-384.

Kahneman, D., Knetsch, J. L. and Thaler, R. H. (1986). "Fairness and the assumption of economics". *Journal of Business*, 59(3): 285–300.

Kimes S. E. (1989). "The Basics of Yield Management". *The Cornell Hotel and Restaurant Administration Quarterly* 30(6): 14-19.

Kimes, S. E. (2002). Perceived fairness of yield management. *Cornell Hospitality Quarterly*, 43(1), 21.

Kosová, R., Lafontaine F., and Perrigot R. (2013). "Organizational Form and Performance: evidence from the hotel industry". *Review of Economics and Statistics*, 95(4): 1303-1323.

Kotler, P., Burton, S., Deans, K., Brown, L., and Armstrong, G. (2015). *Marketing*. Pearson Higher Education, AU.

Leung, D., Law, R., Van Hoof, H., and Buhalis, D. (2013). "Social media in tourism and hospitality: A literature review". *Journal of Travel & Tourism Marketing*, 30(1-2): 3-22.

Li, J., Granados, N. and Netessine, S. (2014). "Are Consumers Strategic? Structural Estimation from the Air-Travel Industry", *Management Science*, 60: 2114-2137

Mathies C., Gudergan S.P., Wang P.Z. (2013). "The Effects of Customer-Centric Marketing and Revenue Management on Travellers' Choice". *Journal of Travel Research*, 52(4): 479-493.

Mauri A.G. (2012). *Hotel Revenue Management. Principles and Practices*. Pearson Italia.

McAfee, P and te Velde, V. (2007). Dynamic Pricing in the Airline Industry, in *Handbook on Economics and Information Systems*, Ed: T.J. Hendershott, Elsevier, Volume 1.

McGill, J. and Van Ryzin, G. 1999. "Revenue Management: Research Overview and Prospects". *Transportation Science*, 33(2): 233-256.

Nelson, P. (1970). "Information and consumer behavior". *Journal of political economy*, 78(2), 311-329.

Noone, B. M., & Mattila, A. S. (2009). "Hotel revenue management and the Internet: The effect of price presentation strategies on customers' willingness to book". *International Journal of Hospitality Management*, 28(2), 272-279.

Oliver, R.L., Swan, J.E. (1989). "Consumer perceptions of interpersonal equity and satisfaction in transactions: a field survey approach". *Journal of Marketing*, 53(2): 21–35.

Orbach, B. Y., & Einav, L. (2007). "Uniform prices for differentiated goods: The case of the movie-theater industry". *International Review of Law and Economics*, 27(2), 129-153.

Phillips, P., Barnes, S., Zigan, K. and Schegg, R. (2016). "Understanding the impact of online reviews on hotel performance: an empirical analysis". *Journal of Travel Research,* forthcoming.

Salanti A., Malighetti P., and Redondi R. (2012). "Low-cost pricing strategies in leisure markets". *Tourism Management*, 33:249-256.

Selmi N, Dornier R. 2011. "Yield Management in the French Hotel Business: an Assessment of the Importance of the Human Factor". *International Business Research*. 4(2):58-66.

Sweeting, A. (2012). "Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets". *Journal of Political Economy*. 120(6):1133-1172

Talluri KT, van Ryzin G. (2004). *Theory and Practice of Revenue Management*. Springer: New York.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. 1st Ed., MIT Press, Cambridge MA.

Xia L., Monroe K.B., Cox J.L. (2004). "The Price is Unfair! A conceptual framework of Price Fairness Perceptions". *Journal of Marketing,* 68 (October):1-15.

Zbaracki MJ, Ritson M, Levy D, Dutta S, and Bergen M. (2004). "Managerial and customer costs of price adjustment: Direct evidence from industrial markets". *The Review of Economics and Statistics,* 86(2): 514-533.

Table 1 – Number of hotels by destination, period of stay and star classification.

	Stars	*Apr-Jun14*	*Jul-Aug14*	*Sep14*	*Apr-Jun15*	*Jul-Aug15*	*Sep15*
Sardinia	1	1	-	-	-	1	-
	2	3	2	4	3	2	2
	3	96	94	100	106	97	101
	4	89	98	98	94	89	85
	5	12	15	15	15	16	15
	Total	201	209	217	218	205	203
Sicily	1	2	3	-	3	3	3
	2	17	16	15	19	17	15
	3	74	72	66	86	86	82
	4	56	59	55	62	64	65
	5	10	10	10	11	10	10
	Total	159	160	146	181	180	175
Corsica	2	28	27	28	29	28	30
	3	85	84	85	92	92	92
	4	24	24	24	27	25	26
	5	6	6	6	7	6	8
	Total	143	141	143	155	151	156
Balearics	1	39	28	38	39	32	38
	2	57	53	56	55	45	56
	3	128	116	116	134	112	116
	4	117	116	111	140	123	110
	5	14	15	16	19	16	16
	Total	355	328	337	387	328	336

Table 2 – Mean price of a double room in hotel by period of stay and star classification

	Stars	*Apr-Jun14*	*Jul-Aug14*	*Sep14*	*Apr-Jun15*	*Jul-Aug15*	*Sep15*
Sardinia	1	49.0	-	-	-	61.0	-
	2	52.8	62.3	58.4	50.2	78.7	57.2
	3	62.0	84.0	65.5	53.7	82.3	59.3
	4	99.5	159.0	123.5	97.0	148.6	114.4
	5	173.5	395.0	280.1	227.4	440.3	234.5
	N	88,411	65,574	39,202	41,744	52,195	23,998
Sicily	1	58.1	70.4	-	44.3	58.0	52.4
	2	62.0	73.0	70.7	50.1	66.6	62.0
	3	76.1	82.2	74.4	64.4	76.0	69.9
	4	121.0	124.2	119.7	100.5	109.0	108.0
	5	228.9	246.3	276.8	214.2	222.1	218.5
	N	50,783	67,679	22,757	30,118	52,720	20,364
Corsica	2	65.5	74.8	63.1	52.9	65.7	57.6
	3	95.2	107.9	93.7	78.0	98.4	84.5
	4	188.9	207.4	185.4	146.5	209.1	158.1
	5	311.0	395.5	317.6	241.0	277.5	243.9
	N	23,279	43,809	26,001	30,709	39,423	16,232
Balearics	1	41.3	65.9	45.0	30.0	56.3	41.0
	2	45.9	69.8	56.2	36.5	59.3	44.4
	3	71.9	103.6	98.3	55.2	86.6	73.8
	4	109.8	149.1	137.0	95.1	133.3	120.4
	5	224.2	279.7	245.0	163.9	292.6	231.4
	N	78,406	100,247	42,777	58,828	63,053	33,467

Table 3 – Percentage of observations with price variation between two consecutive booking days, by period of stay and star classification

	Stars	*Apr-Jun14*	*Jul-Aug14*	*Sep14*	*Apr-Jun15*	*Jul-Aug15*	*Sep15*
Sardinia	1	0.0	-	-	-	2.7%	-
	2	7.5	4.2%	14.6%	3.6%	20.8%	9.9%
	3	8.4	11.6%	14.7%	7.9%	13.6%	12.5%
	4	14.2	21.1%	23.6%	18.4%	31.1%	26.5%
	5	9.5	25.6%	19.8%	42.2%	58.5%	40.2%
	Total	10.6	17.2%	19.1%	14.1%	24.9%	20.4%
Sicily	1	12.1	0.0%	-	2.7%	0.9%	2.8%
	2	9.0	6.5%	12.4%	6.6%	13.0%	9.5%
	3	10.3	11.2%	14.8%	10.9%	13.8%	13.0%
	4	13.2	17.8%	20.9%	22.1%	23.3%	23.6%
	5	27.5	38.8%	34.3%	42.7%	44.0%	45.8%
	Total	12.5	15.7%	18.4%	15.6%	19.7%	19.1%
Corsica	2	5.7	9.8%	9.2%	5.0%	10.4%	14.5%
	3	8.9	12.6%	12.4%	12.8%	19.5%	17.4%
	4	12.1	19.5%	18.1%	30.5%	43.9%	33.9%
	5	17.7	27.3%	22.9%	38.2%	53.0%	43.1%
	Total	9.7	14.1%	13.7%	15.7%	24.1%	21.9%
Balearics	1	5.4	8.7%	9.9%	3.4%	8.5%	9.6%
	2	8.0	10.9%	15.6%	5.7%	12.8%	12.1%
	3	11.3	15.5%	19.6%	10.5%	14.7%	14.2%
	4	16.0	21.0%	20.5%	18.7%	26.1%	22.9%
	5	22.9	27.7%	22.5%	28.8%	45.6%	37.6%
	Total	12.3	17.7%	18.6%	12.5%	19.9%	17.2%

Table 4 – Percentage of observations with price variation between two consecutive booking days, by period of stay and booking time

	Booking time	*Apr-Jun14*	*Jul-Aug14*	*Sep14*	*Apr-Jun15*	*Jul-Aug15*	*Sep15*
Sardinia	1-4	10.6%	19.0%	18.6%	21.6%	39.9%	26.1%
	7-20	10.8%	16.0%	19.7%	17.0%	29.7%	26.0%
	25-40	10.7%	18.4%	22.5%	13.7%	23.4%	23.5%
	45-70	8.8%	17.2%	11.2%	8.1%	20.2%	14.4%
Sicily	1-4	13.1%	16.0%	17.1%	24.9%	36.1%	30.2%
	7-20	12.2%	16.4%	19.6%	18.9%	24.0%	23.9%
	25-40	13.0%	14.4%	21.8%	14.8%	17.8%	20.6%
	45-70	10.9%	15.6%	10.4%	9.1%	14.5%	13.1%
Corsica	1-4	9.1%	17.7%	14.4%	22.5%	40.4%	33.2%
	7-20	9.1%	13.8%	14.4%	20.0%	29.3%	28.9%
	25-40	15.7%	12.4%	12.6%	15.0%	22.5%	24.1%
	45-70	5.7%	11.8%	3.4%	8.6%	18.9%	14.9%
Balearics	1-4	11.2%	17.6%	17.2%	21.7%	36.2%	28.5%
	7-20	11.4%	16.4%	18.5%	17.2%	26.4%	24.3%
	25-40	12.7%	16.3%	20.3%	13.6%	20.3%	21.8%
	45-70	10.4%	15.6%	9.0%	8.4%	17.1%	13.0%

Figure 1– Estimated Probability of observing, for each day of stay, at least a price variation over the booking period - by star classification and customer rating clusters.

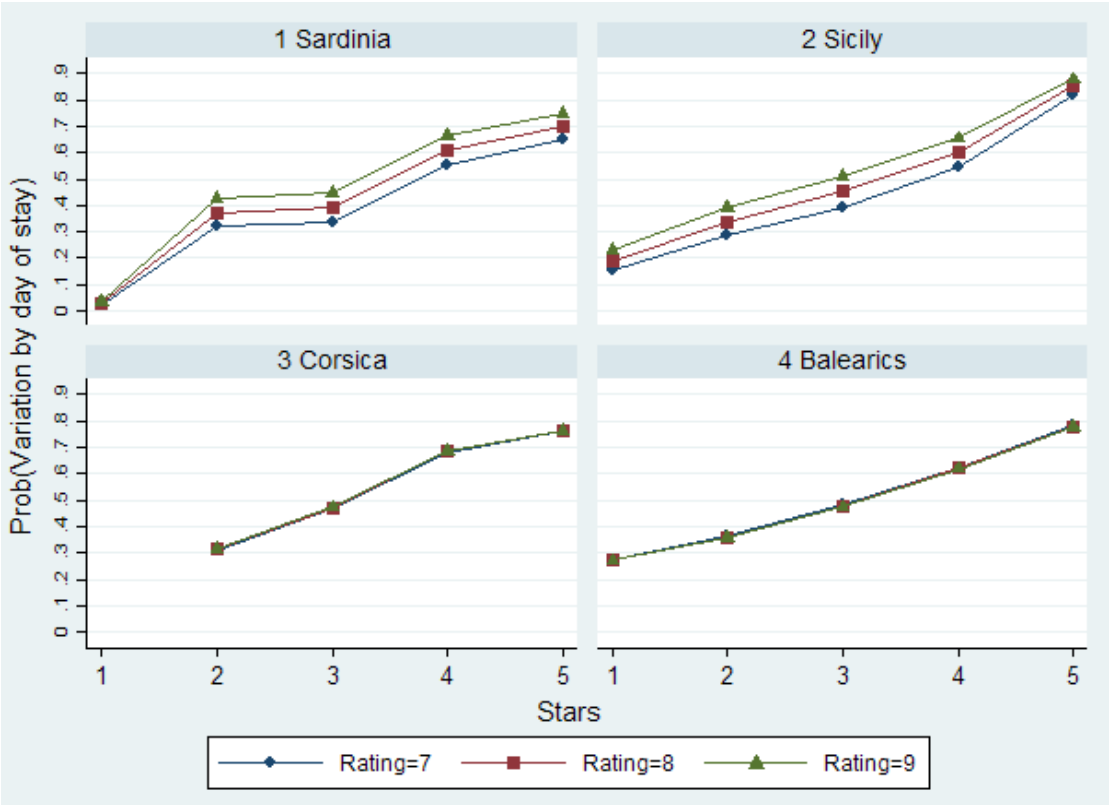


Figure 2 – Estimated Probability of observing, for each day of stay, at least a price variation over the booking period - by star classification and size clusters.

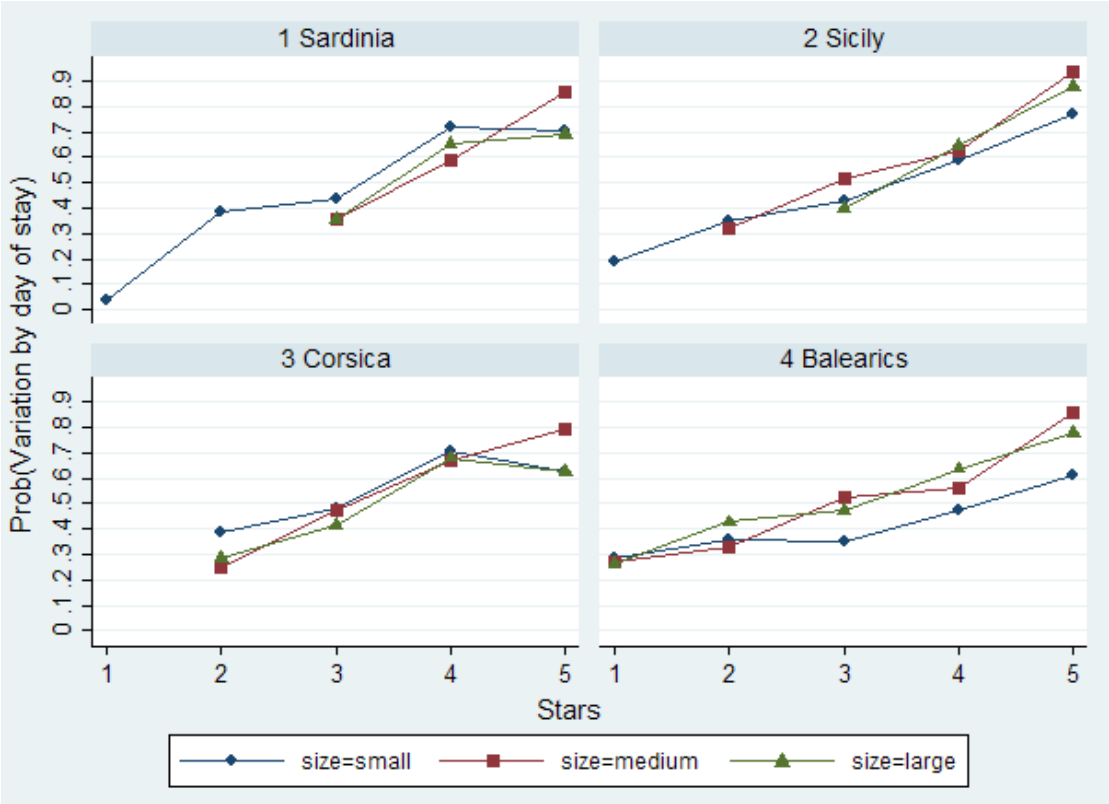


Figure 3 – Estimated Probability of observing, for each day of stay, at least a price variation over the booking period - by star classification and seasonal period.

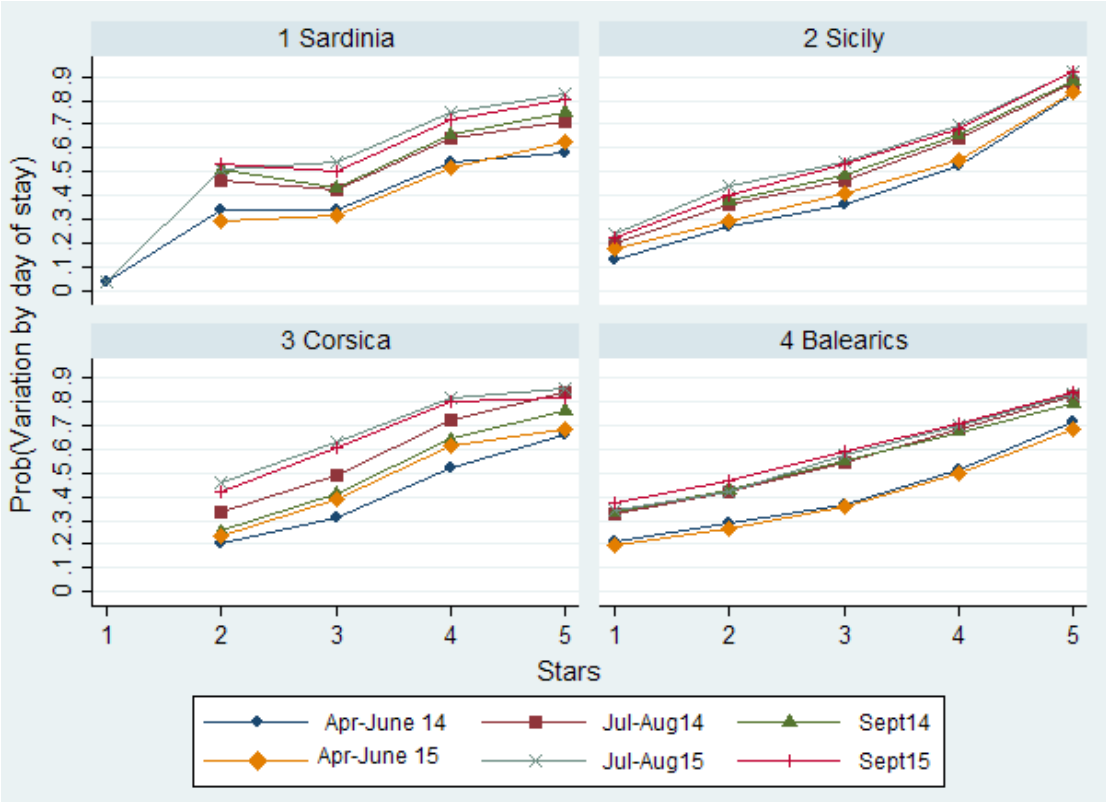


Figure 4– Estimated Probability of a price change over any day of the booking period – by star classification and number of days from query to stay.

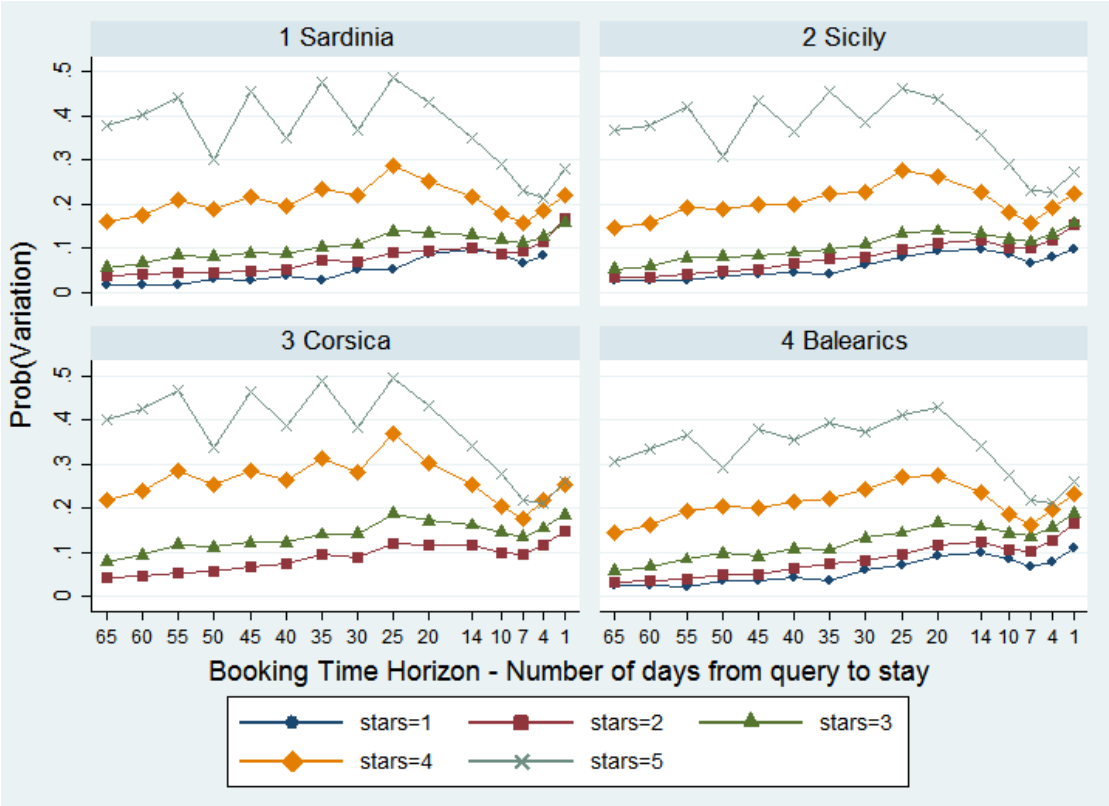


Figure 5– Estimated Probability of a price change over any day of the booking period – by seasonal period and number of days from query to stay.

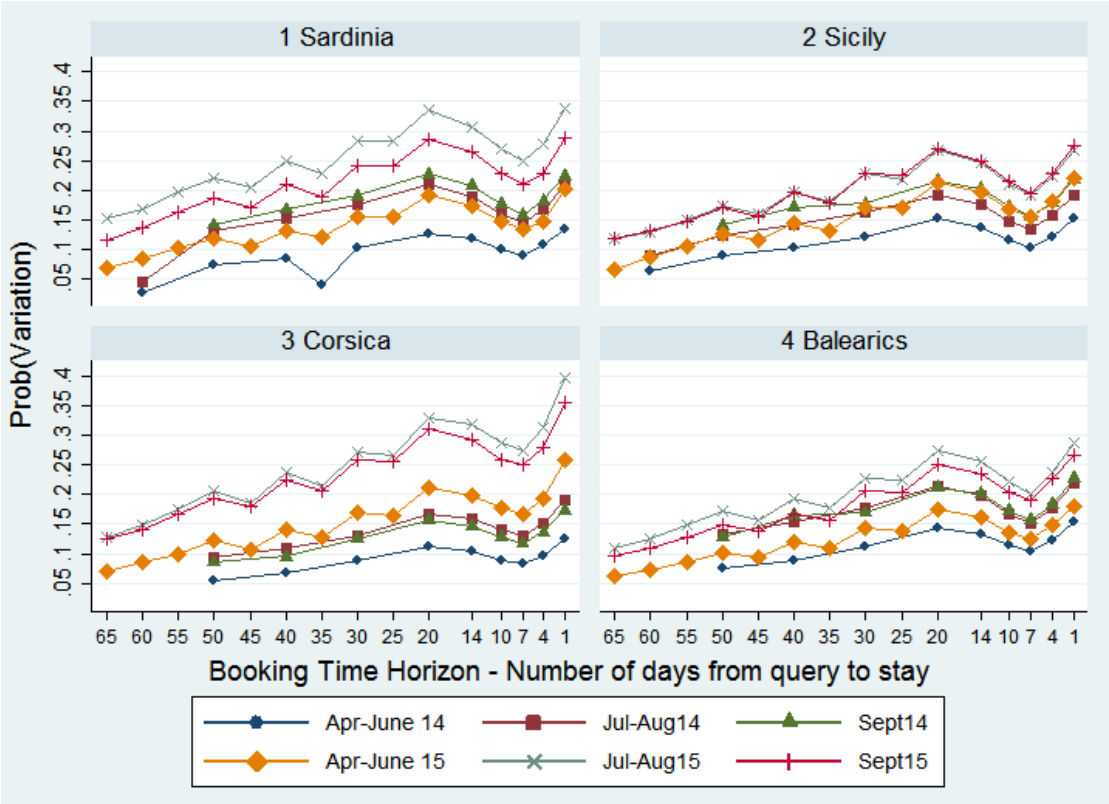


Figure 6 – Estimated probability of a price increase given that a price variation is observed during the booking period. – by star classification and number of days from query to stay.

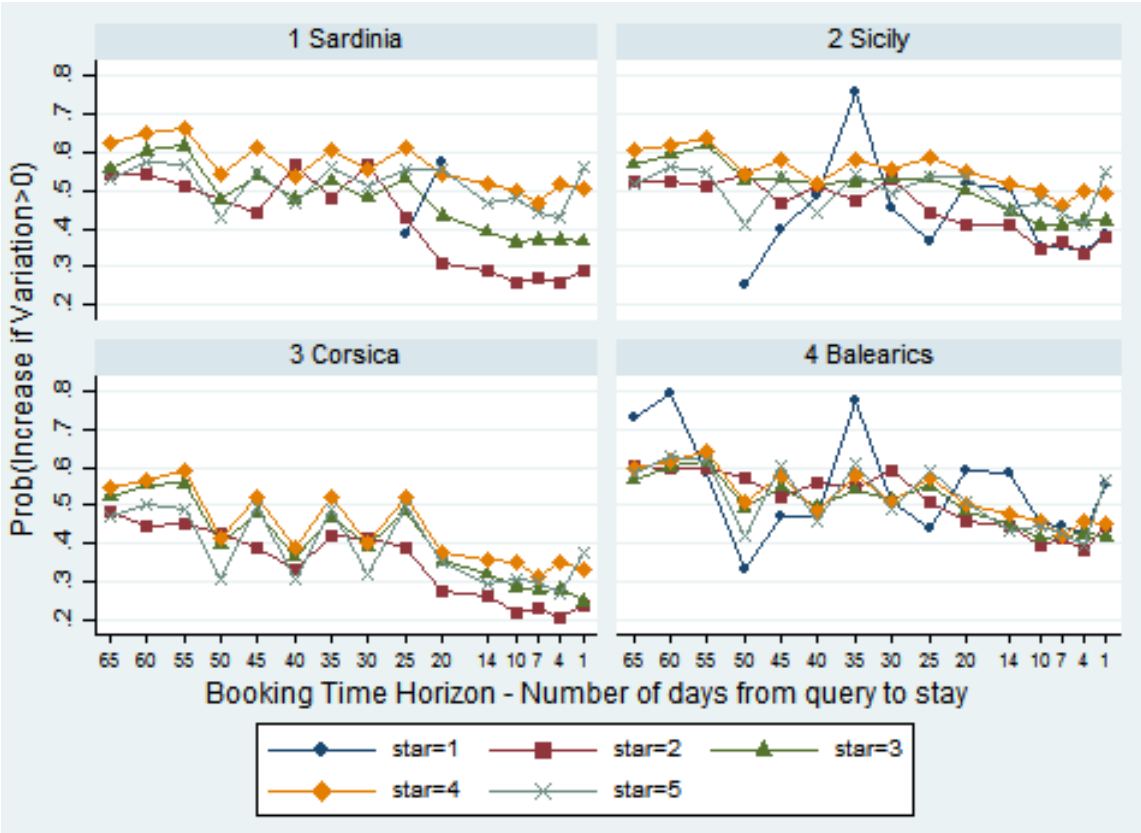
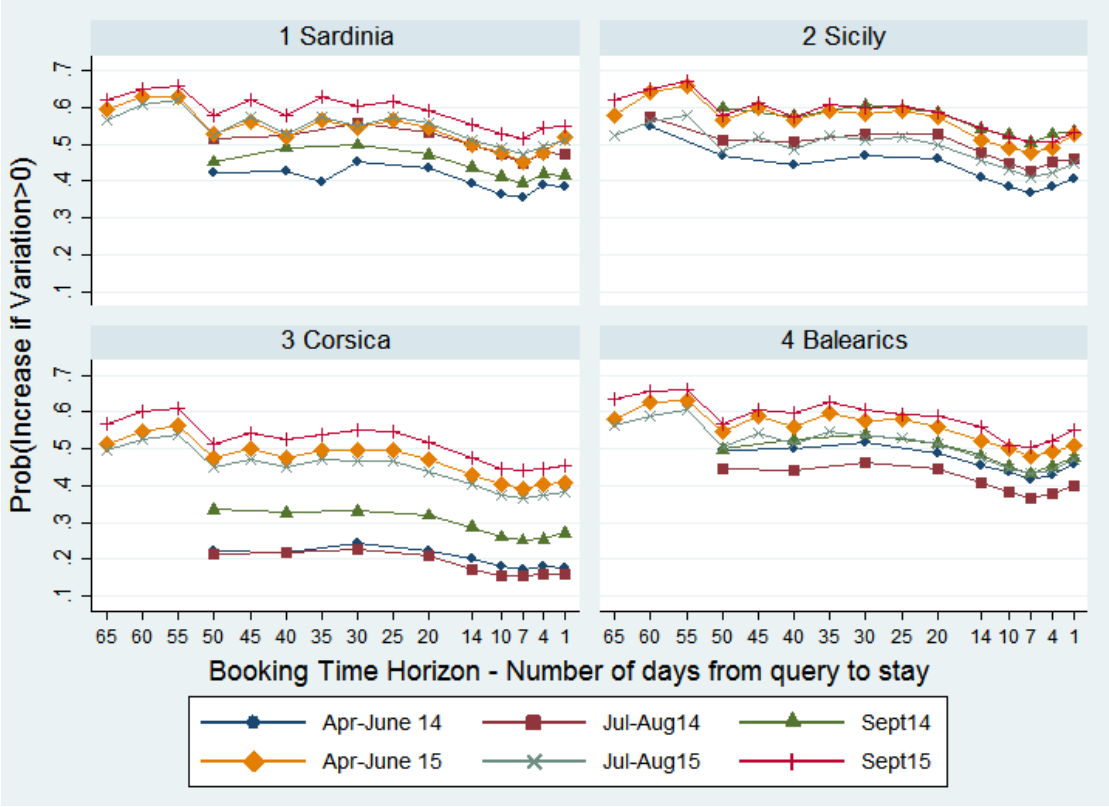


Figure 7 – Estimated probability of a price increase given that a price variation is observed during the booking period. – by season period and number of days from query to stay.



APPENDIX not for publication – List of localities by macro-destination

Sardinia	Sicily	Corsica	Balearics
Alghero	Castellammare del Golfo	Ajaccio	Alcudia
Arzachena	Catania	Bastia	Cala Millor
Baja Sardinia	Cefalù	Bonifacio	Cala Ratjada
Bosa	Noto	Calvi	Cala d´Or
Cala Gonone	Ragusa	Lucciana	Can Pastilla
Cannigione	San Vito lo Capo	L ÎleRousse	Can Picafort
Chia	Siracusa	Porticcio	Ciutadella
La Maddalena	Taormina	Porto Ota	El Arenal
Olbia	Trapani	PortoVecchio	Es Cana
Orosei		Propriano	Ibiza Town
Palau		SaintFlorent	Magaluf
Porto Cervo			Mahón
Pula			Paguera
San Teodoro			Palmanova
Santa Teresa Gallura			Playa d'en Bossa
Villasimius			Playa de Muro
			Playa de Palma
			Port d'Alcudia
			Port de Pollensa
			San Antonio
			San Antonio Bay
			Santa Eularia des Riu
			Santa Ponsa