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Dynamic pricing strategies and customer heterogeneity: the case of European hotels

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Abstract. How much hoteliers do actually make use of dynamic pricing strategies? This work aims at providing some evidence on the actual behaviour of operators in the hotel industry. The empirical analysis is carried out over a sample of almost 1000 hotels distributed around different European capital cities. We collected data for different types of booking days, in particular an intraweek day, usually characterised by the presence of business travellers, and a Saturday, more suitable for a leisure trip. According to the empirical results we demonstrated that more than 90% of fares changed in the period considered, with an inter-temporal structure primarily depending on the type of customer (leisure or business) and on star rating.

Introduction

The perishable nature of hotel rooms is prompting hoteliers to maximise their revenues by trying to achieve optimal dynamic prices with different strategies. On the other hand, customers can strategically change their purchase plans in order to pay as little as possible. In this context, heterogeneity among hotels and customers plays a key role. The best form of inter-temporal pricing strategies depend on the composition of the customer population, such as customer valuations and patience, as stressed by Xuamming (2007). In particular, when *high-valuation customers* have a low degree of patience while *low-valuation customers* are sufficiently patient to wait for sales, setting promotional low prices at the end is preferred. Otherwise, it would be necessary to discourage strategic waiting by high-value customers and set up increasing price dynamics.

The rapid growth of the Internet has had a massive impact on the hotel industry (Law et Tso 2005), however there is a void of published articles in the hospitality literature that examine the trend and the variability of prices in online markets.

This work aims at providing some evidence on the actual behaviour of operators in the hotel industry. How much hoteliers do actually make use of dynamic pricing strategies? If yes, do we observe increasing or decreasing price trends when approaching the check-in date? From the customer perspective, how should they react to the seller's pricing strategies? What are the main drivers behind the structure of the trend of prices?

The empirical analysis is carried out over a sample of almost 1000 hotels distributed around different European capital cities. The idea was observing the evolution of fares concerning a predefined booking day in order to verify the extent of price variability and the significance of any trend. Moreover, we investigate the presence of alternative pricing policies in relation to different characteristics of hotels and potential customers. With respect to the latter, we collected data for different types of booking days, in particular an intraweek day, usually characterised by the presence of business travellers, and a Saturday, more suitable for a leisure trip.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 describes the methodology that clarifies also the data collection. Section 4 presents the main results. Finally, Section 5 offers concluding remarks and directions for future research.

2. Literature review

We analyse both theoretical and empirical contributions by the literature concerning revenue management in hotels and other service industries characterised by finite inventories (such as for example airline seats)

From the theoretical standpoint, Gallego and Ryzin (1994), starting from a general demand function, proved that in some situations it is possible to estimate the exact optimal policy as a function of the stock of rooms and the length of the horizon. Gurion (1995), under the assumption of an aggregate non-linear demand function, offered an optimal market strategic segmentation pricing strategy, by dividing the market into *n* segment to maximize profit. The non-linear approach is confirmed in this field by other authors and proved by more recent analysis. Badinelli (2000) discussed a model suitable for small hotels to determine the optimal solution, given the number of vacancies and based also on time and revealed/hidden market prices. Nevertheless the main concern in applied analysis is the difficulty to obtain the number of vacancies from all the firms operating in such a type of market. Zhao and Zheng (2000) describe the relation between price and time as a non-homogeneous Poisson process. As a main result, if the willingness of a customer to pay a premium for the product does not increase over time, the optimal price decreases over time for a given inventory level, such as in the fashion retail market. However, in the field of hospitality, the customer accepts to pay a premium price. Moreover, Xuanming (2007) takes into account that the customer population is heterogeneous along two dimensions: they may have different evaluations for the product and different degrees of patience. This is a crucial turning point in the literature because his theoretical model delineates that when high-value customers are less patient, markdown pricing policies are effective because the high-value customers would still buy early at high price while the low value customers are willing to wait. On the contrary, when the high-value customers are more patient than the low-value customers, prices should increase over time in order to discourage inefficient waiting. To understand exactly the variables that underpin the price, Qu *et al* (2002) offer a simultaneous equations model suggesting that ‘‘hotel room price level’’ and ‘‘tourist arrivals’’ are significant factors driving the demand for hotel rooms. Equally important, ‘‘hotel room quantity demanded’’, ‘‘room occupancy rate’’, ‘‘last period’s room price’’, and ‘‘labour cost” significantly concur to form the final price.

When considering empirical studies on price dynamics, they are mainly concerned with the airline markets. In a time series of 650 thousand flights for which up to 13 fares available, Piga and Bachis (2006) identified through descriptive statistics that fares do not grow monotonically and, moreover, that a higher volatility of fares in the four weeks preceding the departure date is shown. Noone and Mattila (2008) focused their analysis on the effect of hotel price presentation and they demonstrated, with the ANOVA technique in a sample of 107 people, that the more the price is clear the more the customer wants to buy. They highlighted also a customer tendency to prefer high low rate[1] in the period booked that low high rate and this "bizarre" result needs further investigation.

The analysis on the hotel industry are more concerned with the way of booking and other price discrimination strategies, not necessarily linked with variability over time. This group of papers refers to the difference in booking the same service from different countries, channels, or websites. Yelkur and Da Costa (2001) and Chung and Law (2003) studied the performance of hotel websites according to facilities information, customer contact information, reservations information, surrounding area information, and management of websites. They showed that the bigger the company or the quality is (in term of star ratings), the better in term of information and effectiveness is the website. Piga and Bachis (2005) and Law and Tso (2005) found a significant difference in the amount of money one has to spend to obtain the same service from different distribution channel (local travel agent vs website) or different countries (UK vs Europe). This result is coherent with those obtained in the airline market by Brunger (2010), who combined in a log-lin regression analysis several explanatory variables, such as distribution channel, fidelity, and booking in advance. His results demonstrated that in same market those who book through traditional agencies pay more. This is the so called *internet price* effect. Ellison and Fisher (2005) argued that only one market place, for instance only one website selling a product, allows higher earnings either for the customer or for the company, such as the case of eBay.

[1] Even if the total amount to pay is the same, the result of the ANOVA identifies a preference to choose an high low price than a low high price despite the fact that the average of the amount to pay could be the same.

3. Methodology

The purpose of this study is to quantitatively evaluate the dynamic of online prices of different hotels. Since the beginning of this research project in September 2009, fares information was collected through the Venere.com website, which included all the main hotels in Europe at the time. They offer a "no frills" available fare and this approach was chosen to facilitate comparison among hotels. Furthermore, to reduce the risk of obtaining biased data, and to show such a difference, a sample test with the official website of each hotel was provided.

As a first and necessary step, we checked whether the room price was similar between a generalist channel and the hotel website to strengthen our decision to collect data only with Venere.com. In our test sample, conducted on the hotels in Rome, we confirmed the findings of O'Connor (2002,2003) who argued that "upscale hotel brands were more likely to quote more expensive prices on their own websites than on other channels". In fact, the level of the prices was generally higher in the specific hotel websites. However, the trend of prices, that is the focus of our study, showed very similar patterns for both channels.

Considered the higher volatility of fares in the latest period preceding the accommodation in the hotel, as Piga and Bachis (2006) suggested in the similar field of airlines, we collected fares for hotel staying, respectively, 1, 2, 4, 7, 15, 22, 30, 45, 60, and 90 days from the date of query. The main reason to do so was to satisfy the need to identify the evolution of fares from three months before the booking date.

The dataset includes information about three different queries (01/12/2009, 31/12/2009, and 30/01/2010), each of which in a time series of ten time periods. The first and the third queries are about a single room; the first query is for a room booked on a Tuesday, the third is for a room booked on a Saturday. This approach was chosen to figure out whether there are different strategies between business and leisure travellers. The second query is for a double room at the end of the year. We consider in our dataset several European cities: Amsterdam, Berlin, Bruxelles, London, Madrid, Paris, Prague, Rome, and Vienna. The total amount of hotels analyzed in our sample is 916, as at least one hundred hotels were randomly selected from each city with the exception of Bruxelles which presented a lower amount of hotels. For each hotel detailed information about cities, category (star ratings), zones (city centre vs suburbs) and period were acquired.

It is important to highlight that sometimes it has been impossible to reserve the same room in a hotel from Venere.com in one or more of the periods considered. This could be due to a full load factor or to a particular strategy adopted by the single hotel. To solve this problem we use "an ethical treatment of missing data"[2] as follows.

When one or two missing values were present in the 10 fares of each time series we imputed the average value of the previous and of the next real value in order not to change the underlying trend. On the contrary, when more than two missing values were present we decided to delete the observation. By doing so, we reduced the number of hotels from 916 to 755 for the first booking date, and from 916 to 562 for the third booking date. The second booking date, 31/12/2009, and in general the city of Bruxelles presented significant lacks of data. Therefore, in order to take also into account the different nature of the analysis (single room vs double room), we decided not to consider the group of data referring to the second period in this particular analysis. For the same reason, we omitted Bruxelles from our analysis.

In the present setting, lack of data on a hotel's load factor at the time the fares were retrieved makes it impossible to distinguish the factors behind the temporal price dispersion. Nevertheless the size of our dataset enables us to address several reasons for the observed trend.

4. Data analysis

The data analysis develops in the following steps: (i) we investigate to what extent hoteliers make uses of dynamic pricing strategies by means of descriptive statistics concerning price levels, price variability over the time horizon and box plots referred to specific cities; (ii) we describe the trend of prices by means of linear regressions for each hotel clustering the results according to specific categories; (iii) we use panel data analysis to test the significance of the dynamic trends in our sample.

[2] Barnard and Lan (2008)

Table 1. Descriptive statistics. Check-in date 01.12.10

	N	Mean	St. Dev.
T90	755	102.5	59.4
T60	755	99.9	56.5
T45	755	98.5	56.6
T30	755	97.8	56.7
T22	755	96.3	56.7
T15	755	96.2	58.3
T7	755	97.2	60.7
T4	755	97.4	61.2
T2	755	98.2	62.7
T1	755	97.3	61.8

Table 2. Descriptive statistics. Check-in date 30.01.10

	N	Mean	St. Dev
T90	562	107.0	63.1
T60	562	104.2	61.4
T45	562	102.9	55.7
T30	562	105.6	56.7
T22	562	102.5	63.6
T15	562	107.0	60.0
T7	562	108.1	62.1
T4	562	108.4	62.1
T2	562	108.5	61.8
T1	562	109.2	62.6

Table 1 and Table 2 show the mean fares across all hotels by different booking days, splitted by the two periods considered. Even when using such a highly aggregate measure, some interesting features arise. For the first group (Table 1), the mean price decreases in the period considered. The "advance purchase discount theory"[3] does not stand up in this case. Surprisingly, the second group (Table 2) presents an opposite trend: even in a rather flat manner (that tends to be U-shaped) the trend goes up. The best time to book in a weekend seems to be around three weeks before the date of the query. The latest period before the date of query is risky also because the amount of available hotels decreases implicating a less marked competition of prices among hotels.

[3] Gale and Holmes (1993)

Figure 1. Example of box plot concerning the intraday check-in date

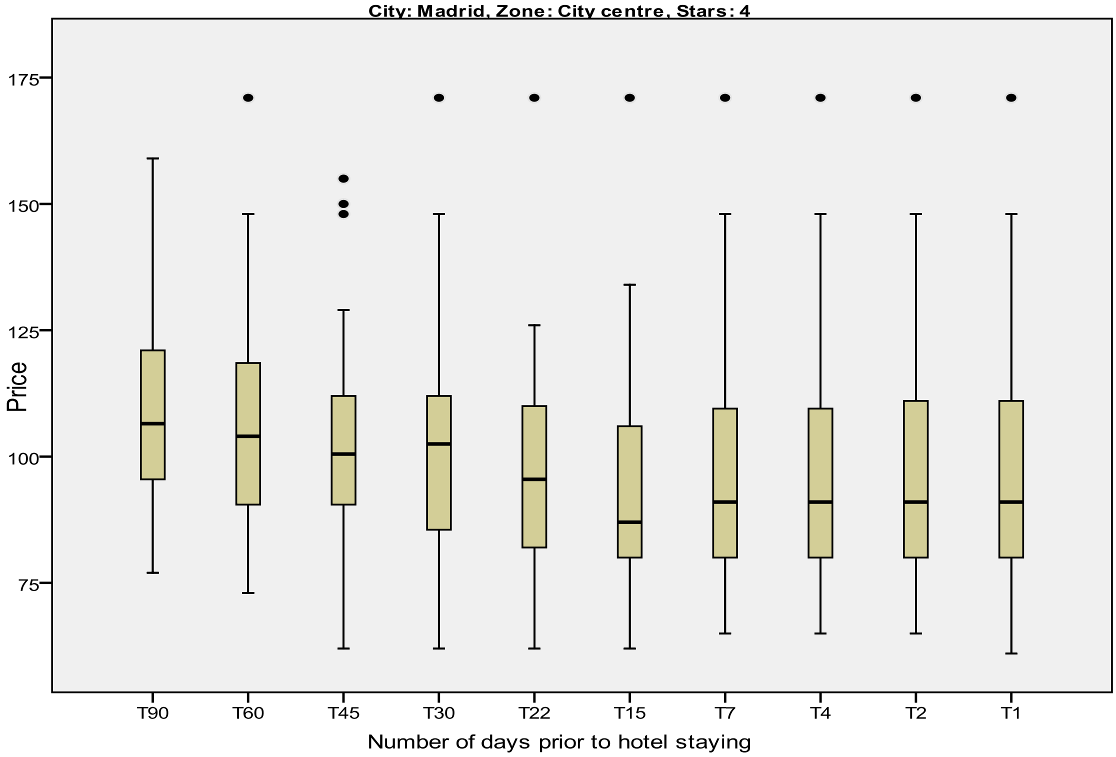


Figure 2. Example of box plot concerning the intraday check-in date

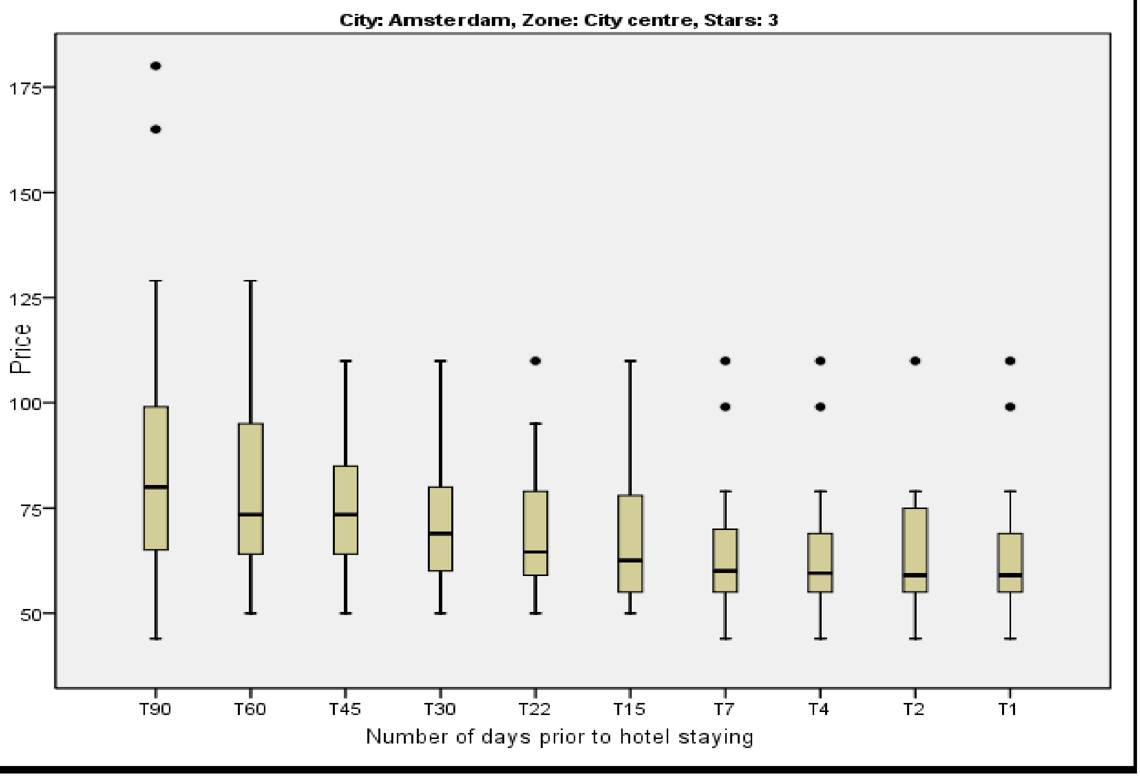


Figure 1 and Figure 2 clearly show how the above described patterns continue to hold when we consider specific clusters. Each box in these figures provides a graphical summary of the distribution of fares for each booking day. We focus on the line inside each box, which represents the median of the distribution (the lower hinge in the box represents the 25th percentile while the top hinge the 75th percentile). It is evident that the trend is decreasing but the monotonic property is sometimes violated. For instance, in Figure 1 the median price available 15 days prior to hotel staying is lower than the median price of the immediately preceding days. Interestingly, fares are consistent in the last week. In Figure 2, a decreasing variability in the period considered is also observed. In addition, even if there are black dots which represent values that are far away from the box, the trend is clearly decreasing in the period considered.

The second group of data, that is the query referring to Saturday 30/01/2010, tells a completely different story.

Figure 3. Example of box plot concerning the weekend check-in date

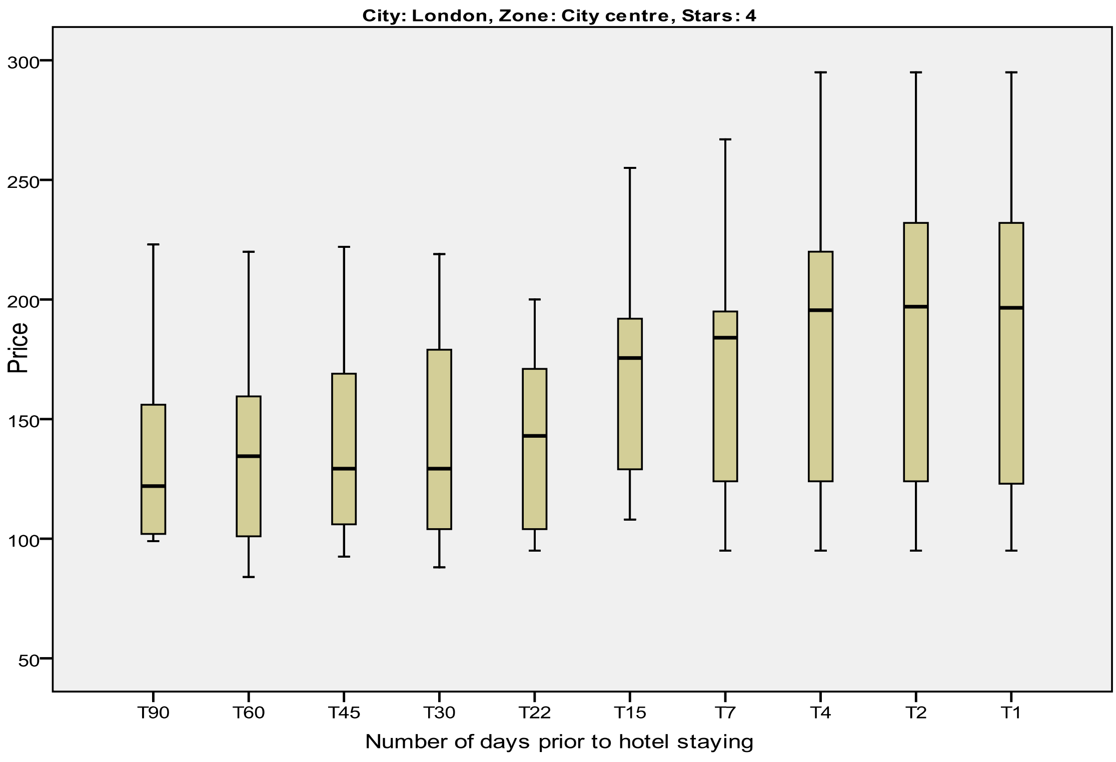
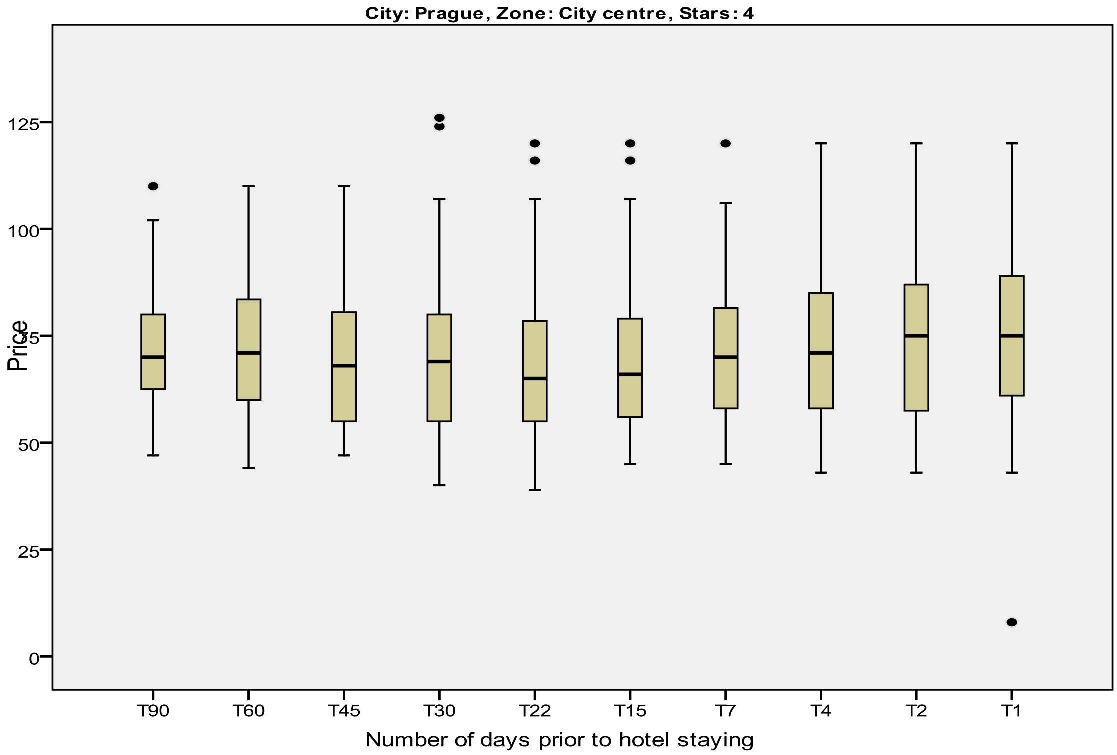


Figure 4. Example of box plot concerning the weekend check-in date



In Figure 3, fares in London present an increasing trend and the variability of fares becomes higher and higher within the booking period. In Figure 4, fares in Prague present a U-shape in a upward way.

The evidence presented so far suggests that in our sample we can identify opposite trends in the two groups taken into account. Although the lack of sales data at each point in time does not permit us to fully understand the reasons behind price dispersion, our findings suggest a complex relationship among fares, load factors, and leisure vs business travellers.

Indeed, arguing that the opposite trends in the two sets of data depend on the different nature of the customer, business in the first case where the query date is a Tuesday and leisure in the second occasion where the query date is a Saturday, seems to be correct. It is also important to note some major differences with respect to the airline sector. Venere.com allows cancelling a reservation without any penalty within 72 hours and, moreover, sometimes it is also possible to reschedule/cancel a reservation later, by negotiating directly with the hotel. Therefore, booking in advance seems not to be the best choice. On this occasion, Mandelbaum, the director of research for PKF consulting, a hotel-industry research agency, states “generally, prices get lower closer to your check-in date as the hotel looks to fill empty rooms”. This assumption could be true for the set of data referring to a working day, the group that we defined as business travellers. On the other hand, our evidence suggests that for the second group of data, mostly leisure travellers, the trend is overall increasing, discouraging a last minute booking. This contrasting evidence may be interpreted in light of the idea of Xuanming (2007), that indicates two specific intertemporal pricing strategies dividing the population according to different product evaluations and degrees of patience. In the case of business travellers, we may attribute to high-value customers a lower degree of patience, since they can be willing to book early at high price in order to choose the preferred hotel in terms of quality. Instead, with a relevant number of leisure travellers, such as in the second selected date in our investigation, it is hard to discriminate high and low valuation customers according to their patience, and this justify a price schedule which is not decreasing.

The analysis of fare volatility allows us to understand the “popularity” of dynamic pricing among operators as well as the relevance of price discounts over time. For this reason, we divided our data according to the coefficient of variation, a compound measure to analyse the standard deviation taking into account the mean of prices.

Table 3. Clusters based on coefficient of variation (CV). Check-in date 01.12.09

	Absolute frequency	Relative frequency	Cumulative Frequency
Stable	82	10,9	10,9
CV less than or equal to 0,1	355	47,0	57,9
CV higher than 0,1 and less than or equal to 0,25	277	36,7	94,6
CV higher than or equal to 0,25	41	5,4	100,0
Total	755	100,0	

Table 4. Clusters based on CV. Check-in date 30.01.10

	Absolute frequency	Relative frequency	Cumulative frequency
Stable	40	7,1	7,1
CV less than or equal to 0,1	274	48,8	55,9
CV higher than 0,1 and less than or equal to 0,25	228	40,6	96,4
CV higher than or equal to 0,25	20	3,6	100,0
Totale	562	100,0	

Table 3 and Table 4 illustrate the coefficient of variation among different hotels in the two periods analyzed. In the first booking date (Table 3), only 11% of times there is no change in fares during the overall period and half of the sample presents a coefficient of variation higher than 0,1.

In the second group of data the variability is present but less marked. The reader can see from Table 4 that the probability of observing a hotel with a coefficient of variation stable or higher than 0.25 is only the 10.7%.

Another step in our analysis consisted in dividing the data into different clusters, in order to reveal some hidden trends. A simple linear regression for each hotel was conducted to disclose the overall trend. According to the results we divided the hotel data into five clusters based on the price trend: decreasing by more than 20%, decreasing by 5-20%, increasing or decreasing at most by 5%, increasing by 5-10%, increasing by more than 20%.

Table 5. Clusters based on price variations. Check-in date 01.12.09

		Decreasing by more than 20%	Decreasing by 5-20%	Increasing or decreasing at most by 5%	Increasing by 5-10%	Increasing by more than 20%	Total
Stars	2	28	28	30	15	8	109
		25,7%	25,7%	27,5%	13,8%	7,3%	100,0%
	3	71	81	75	16	29	272
		26,1%	29,8%	27,6%	5,9%	10,7%	100,0%
	4	71	77	82	49	32	311
		22,8%	24,8%	26,4%	15,8%	10,3%	100,0%
	5	5	15	24	8	11	63
		7,9%	23,8%	38,1%	12,7%	17,5%	100,0%
Total		175	201	211	88	80	755
		23,2%	26,6%	27,9%	11,7%	10,6%	100,0%

Table 6. Clusters based on price variations. Check-in date 30.01.10

		Decreasing by more than 20%	Decreasing by 5-20%	Increasing or decreasing at most by 5%	Increasing by 5-10%	Increasing by more than 20%	Total
Stars	2	4	12	20	4	11	51
		7,8%	23,5%	39,2%	7,8%	21,6%	100,0%
	3	19	43	76	25	33	196
		9,7%	21,9%	38,8%	12,8%	16,8%	100,0%
	4	20	41	97	52	54	264
		7,6%	15,5%	36,7%	19,7%	20,5%	100,0%
	5	2	7	23	14	5	51
		3,9%	13,7%	45,1%	27,5%	9,8%	100,0%
Total		45	103	216	95	103	562
		8,0%	18,3%	38,4%	16,9%	18,3%	100,0%

Table 5 and Table 6 show the distribution of hotels by star ratings (rows) and price trends (columns), for each set of data. In this research one and five luxury stars are bundled together with two and five stars, respectively. In the first set of data (Tuesday, 01/12/2009), two and three stars hotels have a percentage of times in which fares decrease higher than other star categories. The median for these types of hotels decreases in the entire period. The highest quality category presents a more stable trend. In over 38% of 5-star hotels, there is no significant price variation within the overall period. On the contrary, in the group referring to the second booking date (Saturday, 30/01/2010) four and five stars present a stable or increasing trend. For instance, more than one quarter of 5-star hotels show a fare increase between 5% and 10%. Generally, in this group of data, as we anticipated earlier, the volatility is less pronounced.

Finally, the panel data analysis allows strengthening the results by testing the significance of dynamic trend using the whole set of data (see the Appendix for the detailed explanation of the estimation procedure). Coherently with the indications of the descriptive statistics, specific trends were estimated for each booking date and also their relation with the star rating.

Table 7. Summary of the results from panel data analysis

		Estimated Coefficient (p-value)	Comment
Price levels	Difference due to booking date	0.0254 (0.000)	On average, price during the week is higher than in the weekend.
Price dynamic trends	Working Days / High Star Rating Hotels	-0.0068 (0.000)	The trend is negative (thus booking at the last minute is more convenient) when the query is during the week, and this effect is more relevant for low star rating hotels.
	Working Days / Low Star Rating Hotels	-0.0163 (0.000)	
	Weekend/ High Star Rating Hotels	0.0048 (0.000)	The trend is opposite in the weekend (thus booking in advance is better), with an higher increase for high star rating hotels.
	Weekend/ Low Star Rating Hotels	0.0028 (0.001)	

First, we find a significant negative trend when considering the case of working days, suggesting that, from the customer perspective, booking at the last minute is more convenient. This saving opportunity seems to be associated with the business segment, which is more likely to book in a working day. Moreover, the price reduction is much more evident at the lowest star category. In particular, we identified two broad groups of hotels, those with 4 star category or more (defined as "high star rating hotels") and the remaining part (defined as "low star rating hotels"). On average, for low star rating hotels, the estimated effect implies 1.6% price decrease at each of the 10 succeeding observation, yielding an overall reduction of almost 15% of the starting price. This decrease is only partially confirmed (around 6% overall) in high star hotels.

The weekend data shows an opposite trend, thus booking in advance is better, with a more marked evidence for high star rating hotels.

High star rating hotels present an incremental trend. In a decreasing scenario they present more consistent fares. On the opposite when prices rise in the overall period, like in the second booking date, they show a more pronounced increase. This different behaviour could be related to the different nature of hotels: low star categories tend to capture a quantitative wide segment of customers also at the end of the period, while high star rating hotels protect their image without presenting intensive discount in the period immediately preceding the query.

An additional possible explanation of the opposite trend between the first and the second booking date is offered by watching at the opposite level of prices at the beginning of the booking period. In fact the first booking date is characterized by a higher level at the beginning, while the second booking date, which presents an increasing trend, has a lower starting point.

5. Conclusions and future research

Through a better understanding of the online pricing practices, hotel management room distributors can effectively manage the online market, leading to the capture of a high valuation customer.

This research tries to cover a gap in literature, investigating not only the customer perspective but also the relationship between online pricing strategies and the interest of suppliers of hotel rooms. According to the empirical results we demonstrated that more than 90% of fares changed in the period considered, with an inter-temporal structure primarly depending on the type of customer (leisure or business) and on star rating.

When we are considering days during the week (what we defined as *high business value*) the best time to book seems to be the period immediately preceding the hotel staying, while the situation is rather more complicated in a weekend (U-shaped, with a tendency of price increase[4]), when the number of *leisure customers* is predominant. The presence of significant trends which are heterogeneous according to the period of booking and the hotel characteristics, such as star ratings, is confirmed by means of panel data techniques.

The results in this paper can be extended in three broad directions. The first direction is to investigate the relation between price dynamics and occupancy rates. In

[4] In our empirical analysis the best time to book in a weekend is around three weeks before the date of the query. The latest period before the date of query is risky also because the amount of available hotels decreases implicating a less marked competition of prices among hotels.

this paper, the latter information is not available. It would be interesting to consider price decisions, having occupancy rates from three month before the date of query. Mannix (2008) suggested an historical database, owned by Hotelligence and Smith Travel Research, which contains historical information about some occupancy rates.

The second is to have data referring to more booking dates. On this occasion, Piga and Bachis (2006) used an electronic spider which connected directly to the website of the source of data, saving time and giving the chance to analyse a longer trend. Our analysis, in fact, has an impressive number of hotels but to strengthen the results it could be beneficial to increase the number of booking dates.

Finally, to have a more comprehensive examination of the online pricing practices it would be interesting to analyse what there is behind occasional missing values. Is it due to a full load factor or is it simply a strategic strategy adopted by the hotel?

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Methodological Appendix. Panel data analysis.

Let i be the subscript indicating an hotel in our sample, with i = 1 to 778. For each hotel, the price proposal (P) was observed with reference to different check-in dates (subscript d = 0,1) and progressively at 10 different time distance from the date of the query (90, 60, 45, 30, 22, 15, 7, 4, 2, 1 days from the date of query). Let t = 0 to 9 be the subscript indicating each progressive observation (independently from the actual number of days of advance booking). The structure of the panel is unbalanced in the dimension d, since in some cases the hotel was not available for booking.

The panel data analysis allows us to test the trend of price by exploiting the whole sample but at the same time taking into account the specific characteristics of each hotels (or group of hotels) affecting price levels and, eventually, variation.

A general form of the equation can be written as follows:

$$\ln P_{idt} = \alpha + \beta D_d + \gamma Z_i + \omega t D_d S_i + \mu_i + \varepsilon_{idt}$$

The dependent variable P has been transformed in logarithm, in order to interpret estimated coefficient in terms of percentage impact on price. D indicates the dummy variables referred to the two different check-in dates; because of collinearity with the constant term, β is a vector composed of a number of parameters that is equal to the number of booking days minus one (in our case one). Z indicates hotel specific characteristics which affects price levels (for example, city and zone dummies, hotel star rating): this variables are intended to explain cross-sectional price variability. Instead S indicates hotel specific characteristics which, along with the type of booking date (D), can affect the trend of dynamic prices. The variables in S may or may not coincide with Z (in our case, they will be a sub-sample). The interaction between time, D and S allows the estimation of specific trends for each desired set of combination of hotel characteristics and booking date.

The error term is composed by the panel specific effect (u_i) and the random noise (ϵ_{idt}). The panel specific effect may be random or fixed; in the latter case, the estimation would drop the term γZ_i. Table A1 shows the results from the estimation of random effect model (fixed effect were also tested but random effect model was preferred on the basis of an Hausman test). The fit of the model, as expected, is low when it comes to within variation, since the latter is explained – coherently with the paper's objective – exclusively by means of the price trend, which is imposed as fixed among the (four) groups of hotels identified. Nevertheless, the estimated trends are strongly significant. The four specific trends estimated are generated from the interaction between the two type of booking date (D) and two clusters of hotels identified by the star category: the first one (Z_{SH}) including high star rating hotels (at least 4 stars) and the second one including the remaining part (less than or equal to 3 stars).

Table A1. Random-effect GLS regression

Dependent variable is lnP		Number of observations	13170
R-square: within = 0.0495		Number of groups	778
between = 0.6739		Observation per group:	min = 10
overall = 0.6307			avg = 16.9
Wald chi2(15) = 2229.40 (0.000)			max = 20

Regressor	**Coefficient (p-values)**
Constant [i]	3.9921 (0.000)
Booking date dummies	
D_1 (01.12.09 - Tuesday)	0.0254 (0.000)
City dummies	
Z_{C1} (Berlin)	-0.2638 (0.000)
Z_{C2} (London)	0.0121 (0.003)
Z_{C3} (Madrid)	-0.0514 (0.196)
Z_{C4} (Paris)	0.5258 (0.000)
Z_{C5} (Prague)	-0.5132 (0.000)
Z_{C6} (Rome)	0.0983 (0.012)
Z_{C7} (Wien)	-0.1599 (0.000)
Hotel star rating	
Z_{S3} (Star rating = 3)	0.3482 (0.000)
Z_{S4} (Star rating = 4)	0.0121 (0.003)
Z_{S5} (Star rating = 5)	-0.0514 (0.196)
Time effects	
$t * D_1 * Z_{SH}$	-0.0068 (0.000)
$t * D_1 * Z_{SL}$	-0.0163 (0.000)
$t * D_0 * Z_{SH}$	0.0048 (0.000)
$t * D_0 * Z_{SL}$	0.0029 (0.001)

(i) the constant term indicates the average price (in logarithm) in the case of the booking date D_0 (30.01.10 - Saturday) of a two star rating hotel located in Amsterdam.