Sources of Price Elasticity of Demand Variability Among Spanish Resort Hotels: A Managerial Insight

Journal:	*Journal of Hospitality and Tourism Technology*
Manuscript ID	JHTT-11-2020-0298.R4
Manuscript Type:	Refereed Article
Keywords:	Price elasticity of demand, demand function, hotel, pricing, segmentation

Sources of Price Elasticity of Demand Variability Among Spanish Resort Hotels: A Managerial Insight

Design/methodology/approach

The paper estimates online demand functions during high season for seven 4-star resort hotels located at different Spanish destinations. Different price elasticity values are compared and different factors affecting price elasticity are analyzed.

Purpose

The aim of this paper is to use demand behavior estimation to find the sources of price variability among resort hotels at different Spanish destinations.

Findings

The main findings indicate that: (1) most of the high season periods display elastic demands, but factors such as a central location at a resort, recent refurbishments, the availability of additional facilities/services, and a hotel targeted at the couples and/or half-board segments make the demand more inelastic; (2) the Tenerife hotels had the most price-elastic demand; (3) during the closest booking periods to the date of stay, the demand is usually more elastic; and (4) a higher number of local competitors pushes down hotel prices.

Originality/value

The paper highlights the managerial implications of focusing on more profitable demand segments for hoteliers. This is especially useful for the development of revenue management software aimed at improving forecasts.

Key words

Price elasticity of demand, demand function, hotel, pricing, segmentation

1. Introduction

The specific characteristics of the hotel sector, such as perishability, capacity limitations, and demand volatility, make demand and occupancy management basic tools in determining revenue (Anderson and Xie, 2010). Through price variations, a revenue manager can adjust the demand when the available occupancy differs from the occupancy that would maximize revenue. By taking into consideration demand heterogeneity and seasonal fluctuations, some level of customer segmentation is possible. Segmentation is a key instrument in Revenue Management (RM) as it allows customers to be grouped according to price sensitivities (Ivanov, 2014) and interrelations can be established between different segments. The high levels of competition in the hotel sector have led market segmentation to be regarded as a fundamental tool in hotel survival and market success while new technologies have contributed to the apparition of new data sources, allowing new types of market segmentation (Dolnicar, 2020;

Erdem and Jiang, 2016). Among various possible RM strategies, pricing is considered to be flexible and easily adjustable in dynamic, competitive hotel scenarios (Hung *et al.*, 2010).

Mohammed *et al.* (2021) highlight the importance of hotel price differentiation in the hotel sector. Several factors can give rise to demand segmentation and this, in turn, can cause price variability within the same hotel and/or among hotels (Mohammed *et al.*, 2019-a, 2019-b).

Demand function estimation is one of the best ways of determining consumer behavior and their willingness to pay. Lee (2011) and Vives *et al.* (2019) point out that price elasticity of demand can be estimated from a demand function, which is a direct easy way of measuring customer behavior. Elasticity is also an indicator that allows a comparison of customer behavior across different hotels and times (Desiraju and Shugan, 1999), and for customer segmentation (Shy, 2008). Most studies that estimate demand functions rarely show the elasticity values and Vives *et al.* (2019) find a replicable way of estimating the different demand functions across different moments and hotels, allowing for a comparison of price elasticity of demand measures.

Knowledge of demand behavior is crucial in determining revenue, while the capacity to segment the demand can enable hotels to maximize revenue. Hotel demand function estimation allows several questions to be answered that have not been analyzed to date, such as: is the demand more inelastic in the peak season? are customers more insensitive to prices during the closest dates to the date of stay? and which hotel attributes have the potential to attract inelastic demand segments?

By estimating demand behavior, this paper aims to identify the sources of price variability at resort hotels located at different Spanish destinations. To achieve this goal, the study presents an implementation of a demand function model used to estimate own-price elasticity of demand (Vives *et al.*, 2019; Vives and Jacob, 2020) for different resort hotels located at several Spanish destinations.

Hence, the objectives of this paper are: (1) to estimate and compare different elasticity values for the online transient demand for different destinations, seasons, and booking horizons; and (2) to explore hotel locations, specific hotel attributes, and customer characteristics that might explain the differences in elasticities among hotels and destinations. The study's added value is that it boosts knowledge of the demand for resort hotels found in literature, explaining price differences in reservation dates and hotels through customer behavior. The demand function identifies the main factors that affect price elasticities and it has important managerial implications particularly useful in developing RM software for improving forecasts. In fact, no other previous study has carried out such a broad comparison of elasticity values in order to establish price differences across similar resort hotels. In addition, most of the studies in the literature exhibit the hotel attribute effects on the price variable, through hedonic pricing models. However, there are no studies reflecting the effect of these attributes on the elasticity price of demand. This study provides evidence on seven 4-star resort hotels in 5 different Spanish destinations, covering a gap in the literature which focuses mainly on other hotel segments and countries. By estimating and comparing such a broad range of different demand functions for different resort hotels in different areas, the most inelastic demand segments and the hotel attributes with the power to attract the most insensitive demand can be identified.

The empirical application was carried out using data for several resort hotels accounting for over a total of 3,000 rooms, located in 5 destinations in three Spanish regions. All the hotels belong to a leading Spanish multinational hotel chain with more than 120 four and five-star hotels worldwide.

2. Literature review

2.1. A RM approach in the hotel industry

RM is defined in literature as the application of an information system and pricing to ensure the right capacity at the right time in the right place so as to maximize revenue (Ivanov, 2014). Given the hotel sector's characteristics, there is substantial potential for managing demand and occupancy over the booking horizon in order to predetermine hotel revenue. The essence of RM is to understand the value that different customer segments place on hotel products and to align this with product prices and availability (Cross *et al.*, 2011).

Tourism businesses usually segment the demand using demographic, geographic and psychographic, behavioral and product-related, i.e., seasonality– variables (Camilleri, 2018). Customer segmentation can be defined as the process whereby customers are grouped according to their needs and demand requirements (Ivanov, 2014). The objective of RM is to identify segments whose customers share similar responses to price and marketing variations.

2.2. Hotel demand and price elasticity

Several sources of price variability influence hotel customer segmentation and hence hotel pricing. Knowledge of consumer behavior and the possibility of measuring customer willingness to pay are useful tools in segmenting the demand. Through demand function estimations, demand changes under different market conditions and price levels can be measured, i.e. customer willingness to pay, and this is a powerful method of hotel revenue maximization (Lee, 2011). Once a hotel is able to differentiate market segments, it can set different prices for each segment. In fact, the sector deals with different interrelated segments.

Vives *et al.* (2018) observe that most studies estimate aggregate market demands instead of individual hotel demand behaviors. Vives *et al.* (2019) point out that most studies are static across time as demand is only segmented according to distinguishing features of hotels, i.e., the hotel type or category (Lee, 2011), and the estimations usually lead to inelastic demands (Bayoumi *et al.*, 2013; Lee, 2011). However, they find that the resort hotel demand is fairly elastic and that the own-hotel price elasticity values vary across the seasons and booking time. In fact, hotels located at the same destination display completely different demand behaviors. Vives and Jacob (2021) observe that the booking horizon and price elasticity of demand directly affect optimal hotel pricing, while hotel characteristics like the hotel size and location and guest profiles are key factors in determining the price elasticity of demand. Vives *et al.* (2019) and

Mohammed *et al.* (2021) find that last-minute booking prices usually rise as the date of stay draws closer, while the demand is segmented according to different hotel characteristics: tangible attributes, reputational variables, and contextual factors. Petricek *et al.* (2020) observe different price elasticity of demand values according to different seasonal factors, such as timeframes like the low/high season, summer months, weekends and individual years. For them, demand increases as prices rise for some periods with a high demand, while the demand is quite insensitive during low season. Chen *et al.* (2015) find that hotel size, chain affiliation and the distance to international airports have some effect on elasticity values.

2.3. The determinants of hotel price segmentation

Vives *et al.* (2018) classify the sources of hotel price differentiation and customer segmentation into internal and external types. Internal segmentation is directly controlled and managed by the RM department. In fact, revenue managers consider several factors to control hotel revenue in the short run. These factors, which are sources of hotel price variability, are: (1) the booking date, as hotels usually limit the number of rooms sold at certain points across the booking horizon in order to keep them for more profitable guests who book at a later date (Aziz *et al.*, 2011); (2) rate fences, usually based on consumption or product-related characteristics (Ivanov, 2014). (3) tourist types; it is important to understand, segment, and align hotel products with tourist perceptions of a product's value (Cross *et al.*, 2011); and (4) seasonality; fluctuations in demand have a significant impact on peak and low-season optimal hotel prices (Gallego and Van Ryzin, 1994).

External segmentation is used to segment customers and it is not directly controlled by the RM department (Vives *et al.*, 2018). It is sometimes related to the diversity of hotel attributes and categories and to customer perceptions of these attributes. In the short and mid run, these hotel characteristics cannot be changed. The hedonic price theory is one of the most common methods used in literature to measure hotel price heterogeneity (Espinet *et al.*, 2003) and to measure the value of hotel attributes. Mohammed *et al.* (2019-a; 2019-b; 2021) find that tangible hotel attributes like the number of rooms, reputation-related variables (chain affiliation and star rating) and contextual factors (such as close competitors and distances to specific areas) affect dynamic hotel pricing.

Literature on demand function estimation in the hotel sector is relatively limited, given that hedonic pricing models are not able to measure different demand behaviors. However, differential pricing may indicate different demand responses to different prices. Demand function estimations could help to confirm whether the differential prices that are set coincide with the price elasticity of demand, i.e., the demand behavior.

Based on this empirical evidence and literature, the following hypotheses can be put forward when the individual demand behaviors of different resort hotels at different destinations are studied:

H_1. The booking time and seasonality affect a hotel's price elasticity of demand. Vives *et al.* (2018) and Vives and Jacob (2020) found that the booking horizon and seasonality are two key factors in demand segmentation and in the determination of different price sensitivities.

H_2. A hotel's characteristics and tangible attributes strongly influence hotel prices and they have an effect on elasticity values. Specifically:

H_{2a} Longer length segments exhibit more elastic values. To attract longer stays, which are usually linked to higher revenue levels, Bayoumi *et al.* (2013) determined that the price must decrease with the length of stay. Aziz *et al.* (2011) used the length of stay in a dynamic pricing model, since it facilitates the differential prices that can maximize revenue. Salmasi *et al.* (2012) analyze how hotel and customer income affect the length of stay at Italian hotels.

H_{2b} The family and all-inclusive demand segments lead to more elastic demands. Juaneda *et al.* (2011) and Latinopoulos (2018) found that the type of board has a significant effect on prices. Vives and Jacob (2020) showed that the customer segment and type of board directly affect optimal prices.

H_{2c} Specific hotel attributes, such as a spa, tend to attract more inelastic demands. In hedonic pricing studies, Abrate and Viglia (2016), Aguiló *et al.* (2003), and White and Mulligan (2002) find that the availability of a spa has a significant effect on prices.

H_{2d} In terms of room numbers, larger hotels tend to display more elastic demands. Mohammed *et al.* (2019a, 2019b, 2021) showed that hotel size is linked to the frequency of hotel price adjustments, i.e., dynamic pricing practices. Balaguer and Pernías (2013) and Thrane (2005) found that hotel size significantly affects prices. Vives and Jacob (2020) show that the larger the hotel size, the lower the prices.

H_{2e} As for the hotel refurbishment factor, Hung *et al.* (2010) showed that a hotel's age has a partially significant effect on hotel prices. Meanwhile, Thrane (2005) found significant effects on prices in hotels built less than 14 years before.

3. Methodology

3.1. Data

The study uses price and booking data for seven 4-star hotels belonging to a multinational hotel chain, two in Majorca (the Balearic Islands), two in Tenerife (the Canary Islands), and three in Malaga, Cadiz, and Huelva respectively (all in Andalusia). Using data for hotels with the same star rating eliminates one of the most important sources of differential pricing (Abrate and Viglia, 2016; Mohammed *et al.*, 2019-a; 2019-b; 2021; Yang *et al.*, 2016).

The hotel chain's RM department provided the reservations database for the study of every hotel, and the booking data was transformed into room nights, as in Vives *et al.* (2019). In total 31,756 observations were used for stays during the 2014-2017 Spanish high seasons (stays between the beginning of June and September 10th). The dataset was obtained from its online hotel booking system and it included the following variables: date of stay, booking period, number of reservations, price, and information on the hotels' attributes and characteristics, such as location, number of rooms and the available facilities and services, as well as customer characteristics like the length of stay, online rating (obtained from the OTAs), type of tourist/board, and nationality.

The highest prices were found during July and August at all the hotels except for the Tenerife ones, because, in the Canaries the summer months are considered mid-season.

[Insert Table 1]

Table 1 describes the characteristics and attributes of all the hotels included in the study; factors that are proven in literature to affect hotel prices.

The specific destination and background context explain part of the hotel prices, together with differences in the demand. In terms of tourist numbers (*Figure 1*), Andalusia received almost 18 million visitors in 2017 (52.5 million overnight stays), a 52% of whom were domestic tourists. Balearic hotels received more than 10 million visitors (70 million overnights), 87% of whom were international tourists, while in the Canary Islands it amounted to almost 10 million tourists (60 million overnights), 81% of whom were international tourists (INE, 2018). Andalusia had the lowest hotel prices while the Balearics had the highest Average Daily Rate (ADR), 3.1% higher than in the Canaries, and 12.8% higher than in Andalusia.

[Insert Figure 1]

As for the level of regional competition, Majorca has 525 hotels (almost 160,000 beds). Malaga has 450 hotels (90,000 beds). Cadiz has 400 hotels (40,000 beds). Huelva has more than 100 hotels (25,000 beds). Lastly, Tenerife has 122 hotels (66,000 beds).

3.2. Demand function

The online transient demand (Q^d), represented by room nights booked online for a specific date of stay (d), can be defined as a function of the price set by the revenue manager (p^d) and the booking time over the booking horizon (r^d). Thus, the demand function is the following:

$$Q_t^d = f\left(p_t^d, r_t^d\right) \qquad (1)$$

Where time: t = 1, 2, …., d.

Time t represents the reservation dates across the booking horizon and d represents the date of stay, i.e., the last observation on the booking horizon.

The specific hotel demand function used will provide the elasticity values and the booking time effects on the online transient hotel demand. It is a linearized Cobb-Douglas demand model used by Vives *et al.* (2019) and Vives and Jacob (2020), where daily room bookings (Q) are transformed into the average number of daily room reservations (q) for each period of time that p is not changed by the RM department over the booking horizon.

$$\ln q_{t'}^d = \alpha_0 + Dummies_{y,\,d,\,b} + \beta_p{\cdot}\ln p_{t'}^d + \beta_r{\cdot}ln\, r_{t'}^d \qquad (2)$$

$$Dummies_{y,\,d,\,b} = \sum_{y\,=\,1,2,,\ldots,Y} \beta_y Dy + \sum_{d\,=\,1,2,\ldots,D} \beta_d Dd + \sum_{b\,=\,1,2,\ldots,B} \beta_b\, Db$$

In this case, t' represents a variable period of time in which p remains constant.

$$t = 1\,, 2 \ldots\ldots\ldots\ldots\ldots\ldots d$$

$$\underbrace{\qquad\qquad}_{t'_1 = p_1}\ \underbrace{\qquad\qquad}_{t'_2 = p_2}\ \underbrace{\qquad\qquad}_{\ldots}\ \underbrace{\qquad\qquad}_{t'_m = p_m}$$

Dummy variables and factors are described in *Table 2*: *y* the year/season when the observation takes place; *d* the date of stay; and *b* the booking period. Reservation dates are usually grouped by month or half month. The booking horizon is divided in two different demand functions.

[Insert Table 2]

The price elasticity of demand (β_p) can be calculated from the demand function. Each demand function is used to estimate the booking behavior at an individual hotel level for each homogeneous period of dates of stay and for uniform booking periods in order to test the effects of prices on the demand. The elasticity measures are used as input for testing the hypotheses in section two.

3.3. Hotel attributes and elasticity values

In the demand function, the hotel attributes and location and some characteristics of the demand segment cannot be isolated since the elasticities are individually estimated. Thus, although the differences in elasticity values are analyzed and compared, these differences may be partly caused by the location, the value that customers place on a hotel's attributes, or different demand characteristics that are not directly measured by these demand functions. To overcome this problem, once the individual hotel demand functions had been estimated, the general weight that these attributes and demand characteristics account for in the elasticity values was checked and compared through several multiple-hotel regressions. Hence, two general ordinary least square regressions were estimated. In both cases, the dependent variables were the elasticity values estimated in the demand functions presented, which vary across hotels, seasons and booking horizons. The two regressions were used to test the hypotheses outlined in section two and, for this purpose, the following two models were defined:

(1) The hotel dummy variables (*DHotel$_h$*) take a value of 1 when the observation belongs to one of the seven specific hotels, where *h= 1, 2, …, 7*, and one of them is the reference hotel. This allows for the estimation of different general hotel effects on the different elasticity values. The regression also determines the effect of the booking period, specific date of stay and year on the elasticities.

$$\beta_{p,t'}^{\ d} = \alpha_0 + Dummies_{y,\,d,\,b} + DHotel_h \ + \beta_r \cdot ln\, r_{t'}^{d} \qquad (4)$$

(2) Variables relating to the hotel attributes and demand characteristics are individually measured. Thus, they are individually incorporated in each regression through the *New* variables.

$$\beta_{p,t'}^{\ d} = \alpha_0 + Dummies_{y,\,d,\,b} + \beta_r \cdot ln\, r_{t'}^{d} + New \quad (5)$$

The *New* set of variables can consist of two types: a continuous variable that changes across hotels, such as the length of stay (Hypothesis 2a) or hotel size (Hypothesis 2d); and a dummy variable dependent on a specific hotel or demand characteristic, comprising hotel specialization in the family and all-inclusive segments (Hypothesis 2b), the availability of a spa (*Da*) (Hypothesis 2c), and hotel refurbishment (Hypothesis 2e).

4. Results and Discussion

4.1. Elasticity demand estimations across time

Overall, from the dummy variables that indicate which effect each hotel has (*Dh*) on the elasticity values (*Table 3*), the hotels in Andalusia display the most inelastic demands: *hotel 5* reduces the elasticity levels by 0.472 in comparison with *hotel 1* in Majorca, while *hotel 6* reduces it by 0.248 and *hotel 7* by 0.138. Tenerife's hotels are slightly more inelastic than *hotel 1*, and *hotel 2* in Majorca is the most elastic of all the hotels (-0.604). In general, the only year with significant coefficients is 2016 (*Dy*), when the demand was slightly more elastic. As for the most elastic periods (*Dd*), they are in July (between -0.356 and -0.699).

[Insert Table 3]

At a more specific level, *Figure 2* compares the different hotel prices along the dates of stay (lines) with the elasticity values estimated in the demand functions (bars). The first hypothesis (H_1) is confirmed, as demonstrated by the elasticity's variability across the high season and booking horizon (Period I, earlier reservations *vs.* Period II, the closest bookings to the date of stay). More specifically, Period I is generally the most inelastic (*Table 3,* on average the coefficient is 0.184 higher).

[Insert Figure 2]

As for hotel prices, in general, higher price levels during the high season imply greater seasonal price variability. Indeed, Gallego and Van Ryzin (1994) indicate that seasonal hotel prices are directly influenced by demand fluctuations. Hence, the two hotels in Tenerife present the lowest price levels during the peak season and the lowest price variability across the different seasons as it is the destination with the most constant tourist flow throughout the year, while the hotels in Majorca and Cadiz achieve the highest prices (*Figure 2*). *Table 3* shows that the higher elasticity values occur in July, although higher price levels usually involve more inelastic demands.

Figure 2 shows that the hotels in Majorca have moderate elastic demand levels during June and the first half of July, the periods prior to the peak season, and then the elasticity becomes unitary for *hotel 1*, while for *hotel 2* the demand becomes progressively more elastic across the peak season. These seasonal divergences between both hotels can be partially explained by differential pricing and the different demand segments covered.

On average, the hotels in Tenerife have the highest own-price elasticities of demand in the study (*Figure 2*). They also display an increasing trend in elasticity across the high season, generally fluctuating between 1 and 2. During the Spanish high season, Tenerife's hotels have the lowest prices because the summer months represent the island's mid-season. It is also worth highlighting that Tenerife is far from the tourists' country of origin, and Yang *et al.* (2016) find that the higher the cost of travel to a destination, the lower the hotel prices.

The hotels in Andalusia display a wide range of elasticities, but they have the most inelastic demands for almost half the seasonal periods. More specifically, *hotel 5* (Cadiz) has inelastic demands in August and at the beginning of June. In the case of the Malaga hotel (*hotel 6*), the area with the highest number of tourist arrivals in Andalusia, the demand is usually more elastic in June and the first half of July, while from the peak season onwards it becomes inelastic. Finally, in Huelva (*hotel 7*), more inelastic demands can be seen during the peak season.

Thus, seasonality is a very important factor, affecting elasticity values in the hotel demand (Hypothesis 1), as found in Vives *et al.* (2019). In fact, Juaneda *et al.* (2011) point out that prices in the hotel resort segment double during the peak season. White and Mulligan (2002) indicate that seasonality could also affect customer assessments of different hotel attributes.

When the booking horizon elasticities are analyzed in *Figure 2,* Period I presented the most inelastic demands when compared with Period II. This result supports Hypothesis 1 (the booking time affects the hotel price elasticity of demand) and it could be explained by the fact that tourists making a reservation in Period I wish to book a hotel on that specific date and at that location, while tourists making a booking at times closer to the date of stay may relax these requirements as they might change destination when prices are too high. Lee (2016) points out that as the date of stay approaches, the perishability effect of the hotel product may lead to price discounts in order to avoid losing revenue from unsold rooms. Similarly, Falk and Vieru (2019) show that hotels set higher prices for online bookings made during early booking periods, while the lowest prices are set for late bookings.

4.2. The relationship between the elasticities and hotel attributes and demand characteristics

The results of *Table 4* confirm the second set of hypotheses. In general, the variables that lead to elastic online demands are the following:

- A longer length of stay (H_{2a}: -0.363). A shorter length of stay pushes down the elasticity price of demand, i.e. customers spending less nights at a hotel are more inelastic. Accordingly, Salmasi *et al.* (2012) find that income has a positive effect on longer lengths of stay, while the price has a negative effect.
- Specialization in the family segment (H_{2b1}: -0.17). Segment specialization is closely related to guests' sociodemographic characteristics, and some specific segments are more price sensitive than others, while the couple segment is more inelastic. Aguiló *et al.* (2003) find that the type of customer traveling to the Balearics is an important factor in the determination of hotel prices.
- Specialization in all-inclusive segments (H_{2b2}: -0.387). The type of board is another kind of customer segmentation. Bed and breakfast and half board demand segments are

more inelastic. Aguiló *et al.* (2001) point out that the type of board is an important factor in explaining price variability in the hotel sector.

- Hotel size (H_{2d}: -0.567): A larger size makes the demand more elastic, and additionally, as larger hotels must sell more rooms, it affects their cost structure and the implementation of certain RM strategies. Mohammed *et al.* (2019a) also note that larger hotels tend to change their prices more often than smaller ones. Balaguer and Pernías (2013) find that larger hotels usually set lower prices, while White and Mulligan (2002) that larger hotels tend to set higher prices.

While the variables that attract a more inelastic demand are:

- Hotels with a spa (H_{2c}: 0.284): Hotels with a spa tend to have higher prices (Abrate and Viglia, 2016). White and Mulligan (2002) highlight the fact that the availability of a spa is the most important price determinant among US hotels.
- A recently refurbished hotel (H_{2e}: 0.393): Refurbishment is a hotel characteristic that makes the demand more inelastic, perhaps because it is correlated with some specific characteristics tied in with renovations. However, due to our small sample, it was not possible to test what these characteristics might be. Espinet *et al.* (2003) find that hotel refurbishment is a potential source of price increases, even though it is not a significant variable at a 5% level. Hung *et al.* (2010) observe that older hotels tend to set lower prices.

[Insert Table 4]

The location also plays an important role in demand and pricing; that is, the area is an important factor in determining prices (Juaneda *et al.*, 2011). In general, of the two Majorcan hotels, *hotel 2* displays the highest elasticity. This hotel presents most of the factors that usually lead to elastic demands, such as a larger size, and a focus on the family and all-inclusive segments, together with other factors that could explain the high elasticity levels, such as a location on the fringes of the resort, lower online ratings, and a focus on the UK market (*Table 1*). In contrast, *hotel 1* is a recently refurbished one, focusing more heavily on the couples and half-board segments, with a central location in the resort and a guest composition with a one-third share of Germans; factors that all make the demand more inelastic.

As mentioned previously, the Tenerife hotels generally displayed highly elastic demands. Apart from their location (both in the same area) and the seasonality factor, neither of them had been recently refurbished (*Figure 2*), a factor that increases their elasticity levels. In general, *hotel 4* has the most inelastic demand. Although the hotel is more heavily focused on the family segment (usually the most elastic), it is a smaller hotel with 100 rooms less than *hotel 3*. It is targeted at the half-board segment (as opposed to *hotel 3*), and it has higher online ratings, and a lower proportion of UK and Spanish tourists, all of which can lead to more inelastic levels.

The hotels in Andalusia generally achieved the highest online ratings. They had all been recently refurbished, they provided a wider range of additional facilities and services, and they had the guests with the shortest length of stay, all of which reduce the elasticity levels. The guest ratio was evenly distributed between the domestic and German markets, which could have opposing effects on the elasticities. More specifically, *hotel 5* showed the highest prices, although it is the only hotel to have a golf course and it is located in the midst of the resort, which would help to attract the most inelastic demand segments. Furthermore, this Andalusian hotel focuses more heavily on the couples' segment, and it has the highest online ratings. *Hotel 6* focuses on the family segment (an elastic factor) and, among the Andalusian hotels, it has the guests with the longest length of stay. However, it presents beauty and wellbeing facilities, which are inelastic factors. *Hotel 7* also focuses on the family segment, with half its guests being Spanish, and it is located in a remote area with the fewest number of tourists. On the other hand, it has beauty and wellbeing facilities, and it is located in a natural area.

Competitive effects may also influence differential hotel pricing, especially among different regions. According to Abrate and Viglia (2016), a higher number of local competitors pushes prices down, while Mohammed *et al.* (2019-a; 2019-b; 2021) find that it explains part of the last-minute price movements in urban hotel contexts. Indeed, this could be one of the reasons for the higher prices of some hotels in Andalusia, such as Huelva and Cadiz, compared to hotels in Majorca and Malaga. Meanwhile, according to Pachon (2007), a hotel's level of substitutability can be a sign of demand elasticity, and so similar hotels in close proximity to one another that focus on different segments can display different prices and/or elasticities, perhaps explaining the seasonal differences among hotels located at the same destination (Majorca and Tenerife).

5. Conclusions

Price variations enable revenue managers to adjust the demand at times when the available occupancy differs from the occupancy that might maximize hotel revenue. Having a better knowledge of sources of price variability will facilitate customer segmentation, a basic step in revenue maximization. In this sense, pricing is considered to be flexible and easily adjustable in the hotel sector's dynamic, competitive environment (Hung *et al*., 2010).

This paper confirms the adaptability and applicability of the demand model by Vives *et al.* (2019) to other hotels, with no other previous study carrying out such a broad comparison of elasticity values in the resort hotel sector. By extending the study to additional hotels with different attributes, in combination with demand behavior estimations, it is possible to identify which characteristics are more influential in leading to higher revenues. This study used online transient demand data for seven 4-star hotels located at different Spanish regions. Although all the resort hotels have similar features, they do have some specific characteristics that differentiate each one from the rest, possibly explaining the different price elasticities. The two-fold way of identifying the main sources of price variability entailed: (1) First, estimating and comparing the different elasticity values across the different resort hotels, seasons and booking horizons; and (2) second, exploring the locations and specific attributes of the hotels and guest characteristics that might explain differences in the elasticities and managerial implications.

5.1. Theoretical implications

The results confirm the study hypotheses, mainly that the booking horizon is an important factor in explaining the heterogeneity in elasticity values. The availability of the different elasticities can help RM departments to segment the demand across the booking horizon more effectively, setting prices that can increase hotel revenue in the short and mid run. In general terms, most of the estimations for the periods between June and September (the traditional high season in Spain) displayed elastic demands, while farthest periods from the date of stay presented more inelastic demands.

The results also show that factors like the availability of spa facilities, recent refurbishments, and specialization in the couples and/or half-board segments lead to more inelastic demands, while the length of stay, specialization in the family and/or all-inclusive segments and a larger size hotel were factors that led to more elastic demands.

Over the booking horizon, the results indicate that the periods farthest from the date of stay have the most inelastic demands. Finally, the number of hotels locally partly explains price differences due to competition among them.

The study fills a gap in the literature as it covers hotels in 5 different destinations and focuses on resort 4-star hotels while most empirical evidence available in the literature focuses on urban and /or luxury hotels and in other countries or in other sectors such as the airline sector. Additionally, the paper reflects the effect of hotel attributes on the price elasticity of demand, something not found in previous literature.

This study proves that the demand function by Vives *et al.* (2019) is easily applicable to other resort hotels, making the model generalizable and the results comparable. These findings might have long-run managerial repercussions for hotels as they allow for the detection of the most inelastic demand segments before the construction, refurbishment or acquisition of a hotel.

5.2. Practical implications

The managerial implications of results are that hoteliers and/or revenue managers should take demand behavior into account in resort hotel pricing strategies; a factor that not only changes across the different seasons and booking horizons, but also according to different customer characteristics and hotel attributes that facilitate customer segmentation. Hence, by considering elasticity values and hotel occupancy, hotel revenue can be maximized.

Knowing the different price elasticities of demand of different customer segments will not only lead to revenue maximization in the short and mid run, but it could also allow hotels to be designed to suit the most profitable segments prior to their construction or refurbishment to include the attributes that attract the most inelastic demand segments. For instance, what is the elasticity of guests opting for a hotel with a spa? The additional revenue that could be achieved can be calculated and compared with the cost of building the hotel. The elasticities could also be used to ascertain which hotel attributes are in greater demand since the Covid-19 crisis, such as sanitary and hygiene measures or products.

5.3. Limitations and Future Research

Further research must focus on tying in demand function models with optimal dynamic pricing estimations for the same hotels, comparing the prices set by hotels with the optimal prices estimated with the demand function, based on optimal dynamics pricing methodologies. As for the study's limitations, one constraint was the lack of available data for competitor hotels, which would have been useful in improving the estimation of elasticities. Second, the study also lacked additional booking information that could be incorporated in the functions, such as the number of guests, room type, board, and cancellation policies, as well as data from the tour operator segment. Third, the study focused on Spanish resort hotels and so the results may be limited to Spain. New evidence on other mature and emerging resort destinations is needed to make the results more generalizable. Finally, Alrawadieh *et al.* (2021) point out that the cost of third-party RM software for hotels is a key barrier in the adoption of sophisticated technologies because only advanced technological software can be used to incorporate the price elasticity of demand in the RM process.

BIBLIOGRAPHY

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

Aguiló, P.M., Alegre, J. and Riera, A., 2001. Determinants of the price of German tourist packages on the island of Mallorca. Tourism Economics 7(1), 59-74.

Aguiló, E., Alegre, J. and Sard, M., 2003. Examining the market structure of the German and UK tour operating industries through an analysis of package holiday prices. Tourism Economics 9(3), 255-278.

Alrawadieh, Z., Alrawadieh, Z. and Cetin G., 2021. Digital transformation and revenue management: Evidence from the hotel industry. Tourism Economics 27(2), 328-345.

Aziz, H.A., Saleh, M., Rasmy, M.H. and ElShishiny, H., 2011. Dynamic room pricing model for hotel revenue management systems. Egyptian Informatics Journal 12, 177-183.

Balaguer, J. and Pernías, J.C., 2013. Relationship between spatial agglomeration and hotel prices. Evidence from business and tourism consumers. Tourism Management 36, 391-400.

Bayoumi, A.E-M., Saleh, M., Atiya, A. and Aziz, H.A. 2013. Dynamic pricing for hotel Revenue Management using price multipliers. Journal of Revenue and Pricing Management, 12(3), 271-285.

Camilleri, M. A. 2018. Market Segmentation, Targeting and Positioning. In Travel Marketing, Tourism Economics and the Airline Product (pp. 69-83). Springer, Cham, Switzerland.

Chen, C-M., Lin, Y-C. and Tsai, Y-C., 2015. How does advertising affect the price elasticity of lodging demand? Evidence from Taiwan. Tourism Economics 21(5), 1035-1045.

Cross, R. G., Higbie, J. A. and Cross, Z. N., 2011. Milestones in the application of analytical pricing and revenue management. Journal of Revenue and Pricing Management 10, 8-18.

Dolnicar, S. 2021. Market Segmentation for e-Tourism. In: Xiang, Z., Fuchs, M., Gretzel, U., Höpken, W. (eds) Handbook of e-Tourism. Springer, Cham.

Erdem, M. and Jiang, L., 2016. An overview of hotel revenue management research and emerging key patterns in the third millennium. Journal of Hospitality and Tourism Technology 7(3), 300-312.

Espinet, J.M., Saez, M., Coenders, G. and Fluvià, M., 2003. Effect on prices of the attributes of holiday hotels a hedonic price approach. Tourism Economics 9(2), 165-177.

Falk, M. and Vieru, M., 2019. Myth of early booking gains. Journal of Revenue Pricing and Management 18, 52–64.

Gallego, G. and Van Ryzin, G., 1994. Optimal dynamic pricing of inventories with stochastic demand over finite horizons. Management Science 40(8), 999-1020.

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.

INE, 2018. Hoteles: encuesta de ocupación, índice de precios e indicadores de rentabilidad. Available in http://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177015&menu=ultiDatos&idp=1254735576863 (Accessed April 13th, 2018).

Ivanov, S., 2014. Hotel Revenue Management: From Theory to Practice. Varna: Zangador.

Juaneda, C., Raya, J.M. and Sastre, F., 2011. Pricing the time and location of a stay at a hotel or apartment. Tourism Economics 17(2), 321-338.

Latinopoulos, D., 2018. Using a spatial hedonic analysis to evaluate the effect of sea view on hotel prices. Tourism Management, 65, 87-99

Lee, S., 2011. Study of demand models and price optimization performance. Doctoral thesis, Georgia Tech Theses and Dissertations, School of Industrial and Systems Engineering. Available in https://smartech.gatech.edu/bitstream/handle/1853/42914/lee_seonah_201112_phd.pdf (Accessed 8 Aug 2016).

Lee, S., 2016. How hotel managers decide to discount room rates: A conjoint analysis. International Journal of Hospitality Management 52, 68-77.

Lee, M., 2018. Modeling and forecasting hotel room demand based on advance booking information. Tourism Management 66, 62-71.

Mohammed, I., Guillet, B.D. and Law, R., 2019-a. Last-minute hotel-booking and frequency of dynamic price adjustments of hotel rooms in a cosmopolitan tourism city. Journal of Hospitality and Tourism Management 41, 12–18.

Mohammed, I., Guillet, B. D. and Law, R., 2019-b. Modeling dynamic price dispersion of hotel rooms in a spatially agglomerated tourism city for weekend and midweek stays. Tourism Economics 25(8), 1245–1264.

Mohammed, I., Guillet, B. D., Law, R. and Rahaman, W. A., 2021. Predicting the direction of dynamic price adjustment in the Hong Kong hotel industry. Tourism Economics 27(2), 346-364.

Pachon, J., Erkoc, M. and Iakovou E., 2007. Contract optimization with front-end fare discounts for airline corporate deals. Transportation Research Part E 43(4), 425-441.

Petricek, M., Chalupa, S., & Chad, K. 2020. Indentation of consumer behavior based on price elasticity: A case study of the Prague market of accommodation services. Sustainability, 12 (9452).

Salmasi, L., Celidoni, M. and Procidano, I., 2012. Length of Stay: Price and Income Semi-Elasticities at Different Destinations in Italy. International Journal of Tourism Research 14(6), 515-530.

Shy, O. 2008. How to Price: A Guide to Pricing Techniques and Yield Management, Cambridge University Press: Cambridge.

Thrane, C., 2005. Hedonic price models and sun-and-beach package tours: The Norwegian case. Journal of Travel Research 43(3), 302-308.

Vives, A., Jacob, M. and Payeras, M., 2018. Revenue management and price optimization techniques in the hotel sector: A critical literature review. Tourism Economics, 24(6), 720–752.

Vives, A., Jacob, M. and Aguiló, E., 2019. Online Hotel Demand Model and Own-Price Elasticities: An Empirical Application to two Resort Hotels in a Mature Destination. Tourism Economics, 25(5), 670-694.

Vives, A. and Jacob, M., 2020. Dynamic pricing for online hotel demand: The case of resort hotels in Majorca. Journal of Vacation Marketing, 26(2), 268-283.

Vives, A. and Jacob, M., 2021. Dynamic pricing in different Spanish resort hotels. Tourism Economics, 27(2), 398-411.

Wu, C-C., Liu, Y-F. and Chen, Y-J., 2012. Consumer responses to price discrimination: Discriminating bases, inequality status, and information disclosure timing influences. Journal of Business Research 65(1) 106-116.

White, P.J. and Mulligan, G.F., 2002. Hedonic estimates of lodging rates in the four corners region. The Professional Geographer 54(4) 533-543.

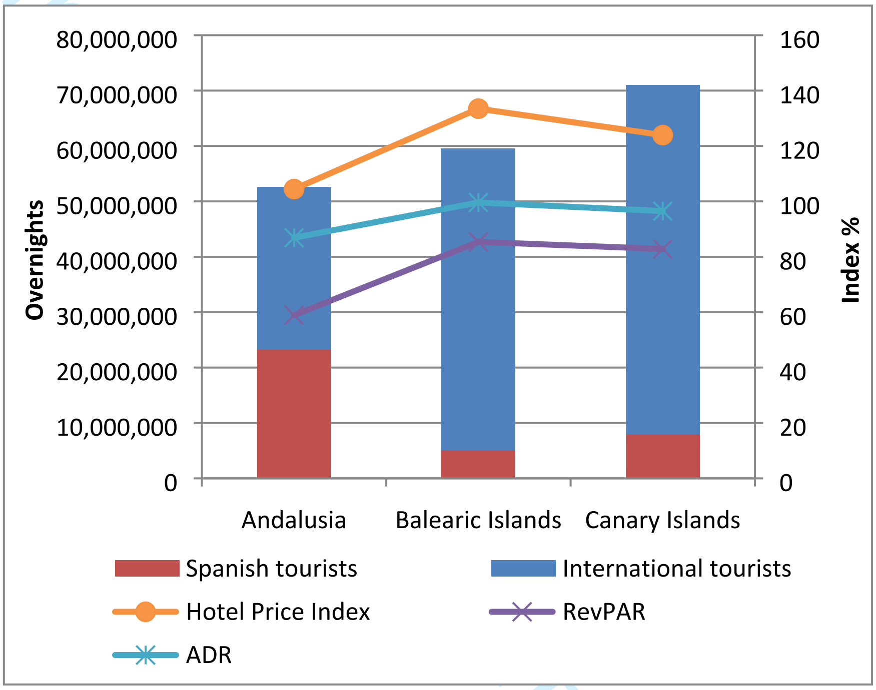
Yang, Y., Mueller, N.J. and Coes, R.R., 2016. Market accessibility and hotel prices in the Caribbean: The moderating effect of quality-signaling factors. Tourism Management 56, 40-51.

Table 1. Hotel characteristics.

Hotel		Hotel 1		Hotel 2		Hotel 3		Hotel 4		Hotel 5		Hotel 6		Hotel 7	
Booking Characteristics	Type of tourist	**Couples**	Families	Couples	**Families**	**Couples**	Families	**Couples**	Families	**Couples**	Families	Couples	**Families**	Couples	**Families**
		60%	27%	13%	**73%**	**46%**	38%	**65%**	22%	**45%**	39%	40%	**51%**	35%	**58%**
			Kids		Kids		Kids		Kids		Kids		Kids		Kids
			16%		31%		16%		7%		20%		19%		22%
	Board	HB	AI	AI		AI		HB	AI	HB	AI	HB	AI	HB	AI
		50%	17%	100%		96%		53%	30%	42%	43%	48%	44%	32%	60%
Tourists nationality		**Germany**	UK	**UK**	Germany	**UK**	Benelux	**UK**	Spain	**Spain**	Germany	**Germany**	Spain	**Spain**	Germany
		32%	19%	**26%**	24%	**49%**	13%	**47%**	12%	**44%**	29%	**29%**	26%	**52%**	14%
Online Bookings		**32%**		**32%**		**31%**		**24%**		**37%**		**35%**		**48%**	
Length of Stay	1-3	6%		15%		6%		12%		18%		15%		19%	
	4-8	59%		51%		64%		53%		56%		55%		59%	
	(+)8	0,35		34%		30%		35%		26%		30%		22%	
	Average (days)	7,93		7,45		7,57		7,61		6,82		7,18		6,57	
Star rating		4		4		4		4		4		4		4	
Room number		360		619		404		505		413		413		300	
Online ratings	Hotel chain webpage	8,8		7,5		8,8		7,5		8,8		8,8		8,8	
	Booking	8,5		8,4		8,7		8,6		9,3		8,5		8,6	
	Tripadv	4,5		4		4,5		4		4,5		4,5		4,5	
Hotel Facilities & Services	Family hotel			X		X						X		X	
	Renewed	X						X		X		X		X	
	Spa	X		X						X		X		X	
	Music & Shows	X		X						X		X			
	Golf									X					
	Gourmet restaurant									X					
	Beauty & Relax					X						X		X	
	Natural area location													X	
Location		Resort heartland		Resort fringe		Resort heartland		Resort heartland		Resort heartland		Resort fringe		Remote area	
		Alcudia		Santanyí		Adeje		Adeje		Chiclana		Torrox costa		Ayamonte	
		Balearic Islands		Balearic Islands		Canary Islands (Tenerife)		Canary Islands (Tenerife)		Andalusia (Cádiz)		Andalusia (Málaga)		Andalusia (Huelva)	

Source: Own Elaboration.
HB: Half board
AI: All-inclusive

Figure 1. Regional breakdown of number of overnight stays in hotels, Hotel Price Index, RevPAR, and ADR, 2017.



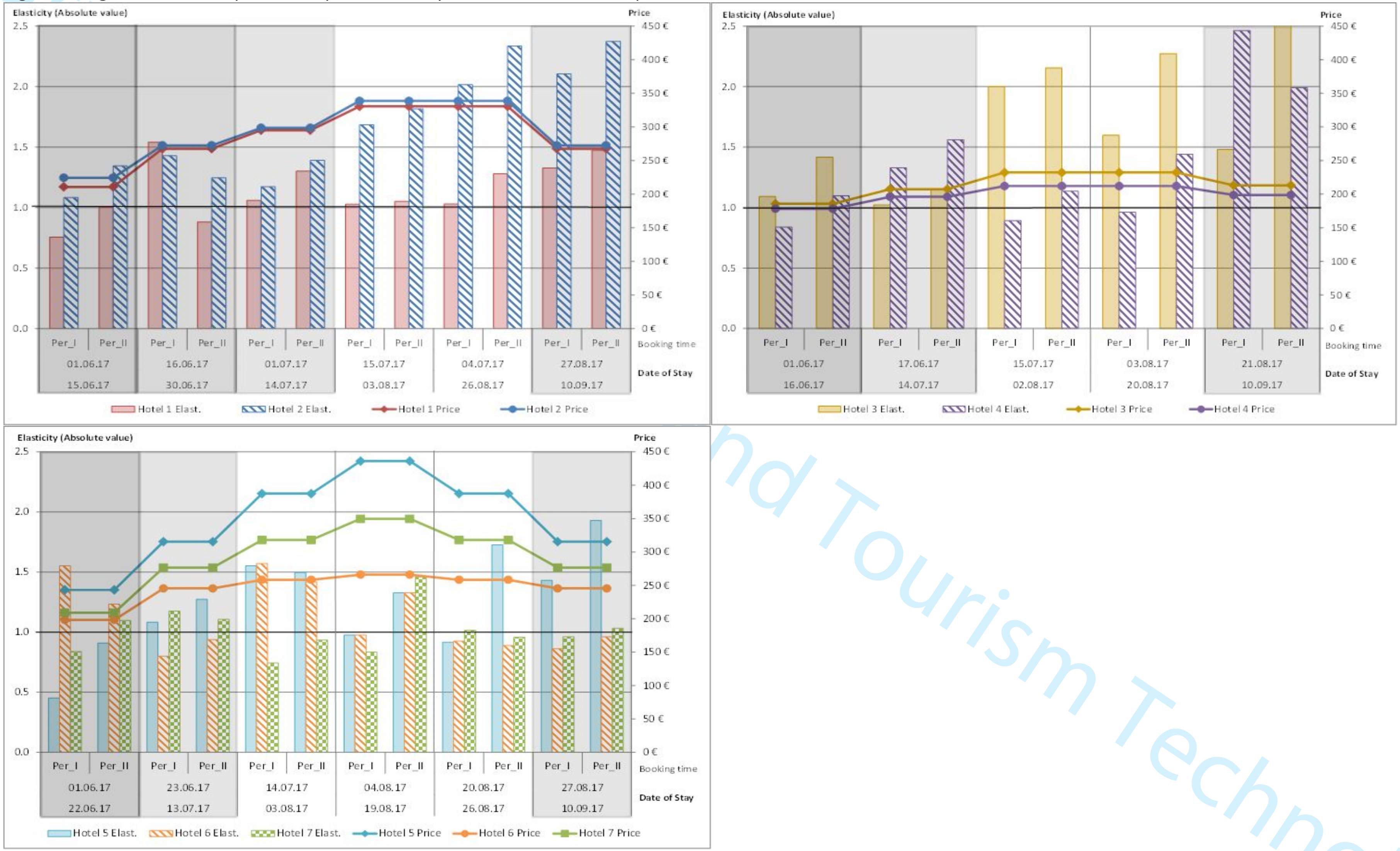
Source: INE (2018)

Table 2. Dummy variables.

Dummy variables		Values	
y	Year/Season	2014 … 2017	
d	Date of stay	d_1+d_2 … $d_{19}+d_{20}$	
b	Booking period	$b_{D-300} \geq b \geq b_{D-270}$ … $b_{D-211} \geq b \geq b_{D-180}$ $b_{D-179} \geq b \geq b_{D-165}$ … $b_{D-119} \geq b \geq b_{D-105}$	*Per I*
		$b_{D-104} \geq b \geq b_{D-90}$ … $b_{D-14} \geq b \geq b_{D}$	*Per II*

Source: Own Elaboration.

Figure 2. High season hotel prices and price elasticity of demand, hotel comparison.



*All the elasticities are significant at the 99% significance level, except for *hotel 5* (14.07-03.08.2017, Per_I) which is significant at the 95% significance level, and for *hotel 6* (20.08-26.08.2017, Per_I & Per_II) which are not significant.
Source: Own Elaboration.

Table 3. Hypothesis 1: Elasticity values variation according to the specific hotel establishment and booking time.

Ind. Var.			Coeff.		Std. Error
Constant			-1.174	***	0.013
Dummy Hotel (Dh)	Hotel 2		-0.604	***	0.007
	Hotel 3		0.107	***	0.007
	Hotel 4		0.075	***	0.008
	Hotel 5		0.472	***	0.007
	Hotel 6		0.248	***	0.008
	Hotel 7		0.138	***	0.007
Dummy year (Dy_y)		2016	-0.015	***	0.006
		2015	0.000		0.006
		2014	0.002		0.007
Dummy date of stay (*Dd_d*)	06-jun	10-jun	0.002		0.014
	11-jun	15-jun	-0.003		0.014
	16-jun	20-jun	-0.138	***	0.013
	21-jun	25-jun	-0.183	***	0.014
	26-jun	30-jun	-0.199	***	0.014
	01-jul	05-jul	-0.356	***	0.014
	06-jul	10-jul	-0.569	***	0.013
	11-jul	15-jul	-0.586	***	0.014
	16-jul	20-jul	-0.695	***	0.014
	21-jul	25-jul	-0.699	***	0.014
	26-jul	30-jul	-0.685	***	0.014
	31-jul	5-Aug	-0.516	***	0.013
	6-Aug	10-Aug	-0.247	***	0.013
	11-Aug	15-Aug	-0.246	***	0.013
	16-Aug	20-Aug	-0.239	***	0.013
	21-Aug	25-Aug	-0.138	***	0.014
	26-Aug	31-Aug	-0.309	***	0.014
	01-sep	05-sep	-0.350	***	0.014
	06-sep	10-sep	-0.334	***	0.014
Period I^d			0.184	***	0.007
$(\ln r^d_{t'})^2$			0.001	***	0.000
Observations			31765		
R^2			0.546		
Adjusted R^2			0.546		
(P-value)			0.000		

* Significant at the 90% significance level.

** Significant at the 95% significance level.

*** Significant at the 99% significance level.

Source: Own Elaboration.

Table 4. Hypothesis 2: OLS regression weight of hotel attributes and demand characteristics variables on elasticities.

Individual Variables		Coeff.	Std. Error
Hotel length of stay	H_{2a}	-0.363 ***	0.006
Family segment Dummy	H_{2b1}	-0.170 ***	0.009
All inclusive segment Dummy	H_{2b2}	-0.387 ***	0.007
Spa Dummy	H_{2c}	0.284 ***	0.006
Hotel Size	H_{2d}	-0.567 ***	0.007
Hotel renewal Dummy	H_{2e}	0.393 ***	0.007

Source: Own Elaboration.

Dear Editor Cihan Cobanoglu,

Herein we enclose a new version of the manuscript Manuscript ID JHTT-11-2020-0298.R3 entitled "Sources of Price Elasticity of Demand Variability Among Spanish Resort Hotels: A Managerial Insight" submitted to the Journal of Hospitality and Tourism Technology, which has been modified according to reviewers' comments and suggestions in third round of reviews. The new paper version accepts the suggestions made by the referees in all rounds.

We hope that with these changes the paper is now suitable for publication.

Looking forward to hear from you soon,

Aldric Vives

Answers to editor's suggestions

1. **Make sure to follow JHTT author guidelines closely: http://www.emeraldgrouppublishing.com/products/journals/author_guidelines.htm?id=jhtt**
   For example, when there are three or more authors, you need to use Adam et al., XXXX (or Adam et al., XXXX) format for the first time and after.

   We have done as editor indicated and revised the manuscript to follow JHTT author guidelines.

2. **Revisit the Discussion and Conclusions sections one more time to better answer the "So What" question. There should be four sub-sections under this section: (1) Conclusions, (2) Theoretical Implications, (3) Practical Implications and (4) Limitations and Future Research.**

   We have revisited the Discussion and Conclusions section to better answer to the "So What" question and sub-divided the Conclusions section into different subsections as indicated.

3. **Cross check all references within text with your reference list. You may like to add more recent and relevant references published in recent months/years in JHTT or other journals.**

   Aa suggested, all references within the text have been cross checked with the reference list. We have included a reference of JHTT (Erdem and Jiang, 2016) in the introduction.

4. **Keep your article below 6000 (max 7000) words including references, tables and figures.**

   The article has now 6996 words, below the maximum of 7000 words including references, tables and figures.

5. **Proofread your article one more time and also you may ask a technical writer/copy editor to proofread it for you. After the manuscript is accepted, we will not ask you to proofread it again. In short, after I send you an official acceptance e-mail, you will not be able to make any further changes in your manuscript.**

   We have proofread the article and a technical writer has also proofread it for us.

6. **Submit a clean version of your paper. You don't need to show/highlight all the changes made in the paper. I will read its final version anyway.**

We have done as suggested, and submitted a clean version of our paper without the changes made in the paper highlighted.

7. **Include a brief report showing how you have responded to the above requests. You don't need to show/highlight all the changes made in the paper. I will read its final version anyway.**

As you may observe in the new version of manuscript, the paper has been summarized eliminating all redundant information, but considering all text that was included due to reviewers' suggestions in the 3 rounds of paper revision. The manuscript now follows all the JHTT author guidelines, especially the format in references have been corrected accordingly. The paper has now 6996 words, below the maximum of 7000 words including references, tables and figures. For example, as we had to shorten the article, Table 1 of previous version of the paper was eliminated in the new version as it did not provide relevant information for the literature review and all text in manuscript related to Table 1 has been eliminated, and tables re-numbered accordingly. Specifically:

<u>Abstract</u>

Purpose was shortened, first sentence eliminated.

<u>Introduction</u>

First paragraph:

- First two sentences of first paragraph were eliminated, redundant information in order to shorten the length of paper.
- The sentences starting "Revenue management …. (Camilleri, 2018)" were removed as these comments appear similarly also in first paragraph of section 2.1.
- Last sentence eliminated, redundant comment.

Second paragraph. Text starting: "Firstly, at an internal level… Vives et al., 2018)" eliminated ad these comments appear in section 2.3.

Third paragraph shortened, several sentences eliminated, especially those referring to the oldest references.

Fourth paragraph, one sentence removed: "However, ..to forecast the demand" as it is not needed to understand the text and follow the thematic thread.

Sixth paragraph of previous version, the text "Not only…. For improving forecasts" removed as these comments appeared in Conclusions, and last sentences starting: "The paper confirms… Hence maximizing revenue", eliminated as they are included in the Literature Review and Conclusions.

Last paragraph explaining the paper's structure eliminated as it is redundant information and papers published in JHTT frequently do not include a paragraph describing the paper's structure.

Literature Review

Section 2.1.

Second paragraph:

- Text starting "Customer segmentation… (Ivanov, 2014), was removed as it is included in other sections of paper and the Ivanov reference as well.
- The sentences at the end: "This helps … a diversity of factors" also eliminated to shorten the paper and include only the most relevant papers for the manuscript.

Section 2.2

First and second paragraphs were also shortened and only the most relevant references for the paper's objectives were considered.

Section 2.3.

First paragraph was summarized and shortened.

Second paragraph, Table 1 was eliminated as explained before and the text referring to Table 1 that was eliminated, was removed from the manuscript. All tables had to be renumbered.

H_{2b} Vives and Jacob (2020) eliminated as it has been used in Discussion as well.

Methodology

First paragraph, some references eliminated t, too many, only the most relevant kept.

Second paragraph, description of information in dataset summarized.

Fourth paragraph removed, not necessary to follow the thematic thread of the manuscript.

Fifth and sixth paragraphs, text describing information on Table 3 (now in current version is Table 2) summarized.

Results and Discussion

Section 4.1.

- Some sentences eliminated, those that were redundant or not so important for the paper's objectives.
- Last paragraph, some references removed, specially the oldest ones, and the most recent left.

Section 4.2.

Reference of Juaneda et al. (2011) removed as other text in the manuscript about it, the same for example, with the references of Espinet et al. (2003) or Aguiló et al. (2001) in third paragraph, among others.

Conclusions

This section was sub-divided into 5.1. Theoretical Implications, 5.2. Practical implications and 5.3. Limitations and Future Research as suggested by editor.