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**REVENUE MANAGEMENT TECHNIQUES IN THE
RESORT HOTEL SECTOR: SEGMENTATION,
DEMAND FUNCTION ESTIMATION AND OPTIMAL
PRICING**

Aldric Vives Maruffy



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The present thesis takes the structure of a PhD by publication.

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- b) Sources of Price Elasticity of Demand Variability Among Spanish Resort Hotels.
Chapter 4.
Vives, A. and Jacob, M.
Under review in a high impact factor Journal

List of acronyms and abbreviations

b: Booking period

d: Date of stay

DP: Dynamic Pricing

HP: Hedonic Pricing

Ht: Hotel

ICT: Information and Communication Technologies

L: Lagrange multiplier method

Max R: Revenue maximization model

MNL: Multinomial Logit

OP: Optimal Pricing

P: Price

Per: Period

Pr: Probability in the Poisson regression model

Q: Daily room reservations

S: Number of days that price remains constant

R: Gap between the booking date and date of stay

RM: Revenue Management

t: Time along the booking horizon

TO: Tour Operator

y: Year/season

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Abstract

In the last decades pricing techniques in hotel management literature have evolved from room inventory controls to a customer behavior orientation approach. The new technologies development and the data availability have allowed the Revenue Management (RM) to focus the research at the individual hotel level. The pricing threshold time effect on hotel performance is an important factor that revenue managers should differentiate in the decision-making process; as price variations due to the demand shifts across the booking horizon, which can vary daily, are not the same as price changes produced by construction works carried out in hotel physical assets, which can only vary at the long-run. In a first step, the present thesis presents a demand function model for resort hotels, which measures the online transient demand when price and booking moment variables change. The first round results show that hotels located in the same destination, which belong to the same hotel chain, are able to display completely different demand behaviors –in terms of price elasticity of demand– which change across the different seasons and booking horizon times. Meanwhile, the second round results point out that seven hotels located in three different Spanish destinations, which also belong to the same hotel chain, present elastic demands during most of the high season periods, but it is found that some hotel factors are able to reduce the elasticity levels –such as the hotel renovation, the supply of additional facilities and services, the belonging to the couple and/or half board customer segments, the higher the proportion of German tourists, or lower proportions of local competitors. And in a second step, the demand functions are adapted to deterministic and stochastic dynamic models that allow the determination of prices that maximize the revenues of two resort hotels located in the same destination –the stochastic estimations are usually more similar to the latest observed data, while the deterministic models usually produce more similar estimations to the average data. The results show that the optimal prices are affected by the distribution of elasticities across the booking horizon, the natural variability of demand, seasonality, and hotel specific attributes, such as the number of rooms available, the hotel location, and the tourist profile. In conclusion, hotels located in the same destination usually present similar pricing policies, due to the fact that in the hotels chains it is usually the same person the one who manages the nearby hotels. Meanwhile, the results highlight that hotels located in the same destination should follow individualized pricing policies, more focused on the specific hotel attributes and tourists characteristics.

Resum

Durant les darreres dècades les tècniques de fixació de preus presents a la literatura de gestió hotelera han evolucionat des d'un control de l'inventari d'habitacions disponibles a un enfocament orientat al comportament del consumidor. El desenvolupament de les noves tecnologies i la disponibilitat de dades han contribuït que la recerca relacionada amb el Revenue Management se centrin cada cop més a nivell d'establiment hotelier. L'efecte de la fixació de preus sobre els resultats hotelers al llarg del llindar de temps és un factor important que els revenue managers han de diferenciar en el procés de presa de decisions; ja que no és el mateix una variació de preus provocada per canvis en la demanda al llarg de l'horitzó temporal de reserves, que pot variar diàriament, que canvis de preus produïts per obres sobre els atributs físics de l'hotel, que només poden variar a llarg termini. En una primera fase, la present tesi presenta un model de funció de demanda enfocat al sector hotelier vacacional, que mesura la demanda online així com va canviant la variable preu i el moment de la reserva. La primera tanda de resultats mostra que hotels situats en un mateix destí turístic, que pertanyen a una mateixa cadena hotelera, són capaços d'exhibir comportaments de demanda totalment diferenciats –pel que es refereix a l'elasticitat preu de la demanda– al llarg de les diferents temporades i moment de la reserva. Mentre que en una segona tanda de resultats, procedents de set hotels vacacionals situats a tres destins espanyols i que també pertanyen a la mateixa cadena hotelera, destaca que presenten demandes elàstiques durant la majoria de períodes de la temporada alta, però es detecta que alguns factors dels hotels poden reduir les elasticitats –tals com la remodelació de l'hotel, l'oferta d'instal·lacions i serveis complementaris, els segments de clients que viatgen en parella i/o consumeixen mitja pensió, la major proporció de turistes alemanys o la menor proporció de competidors locals. I en una segona fase, s'adapten les funcions de demanda a models dinàmics determinístics i estocàstics que permeten la fixació de preus que maximitzen els ingressos de dos hotels vacacionals situats en un mateix destí turístic –les estimacions estocàstiques són normalment més semblants a les darreres dades observades, mentre que els models determinístics normalment produeixen estimacions més semblants als valors mitjos del conjunt de dades. Els resultats mostren que els preus òptims es veuen afectats per la distribució de les elasticitats al llarg de l'horitzó temporal de reserves, la variabilitat natural de la demanda, l'estacionalitat i els propis atributs de l'hotel –tals com el nombre d'habitacions disponibles, la localització de l'hotel i el perfil dels seus turistes. En conclusió, hotels situats en un mateix destí turístic normalment presenten una fixació de preus semblants, atès que en les cadenes hoteleres es normalment la mateixa persona qui gestiona hotels situats a prop. Mentre que els resultats ressalten que hotels situats en un mateix destí haurien de seguir polítiques de preus individualitzades, més enfocades als atributs específics dels hotels i a les característiques dels seus clients.

Resumen

En las últimas décadas las técnicas de fijación de precios presentes en la literatura de gestión hotelera han evolucionado desde un control de inventario de habitaciones disponibles a un enfoque orientado al comportamiento del consumidor. El desarrollo de las nuevas tecnologías y la disponibilidad de datos han contribuido a que las investigaciones relacionadas con el Revenue Management (RM) se centren cada vez más al nivel de establecimiento hotelero. El efecto de la fijación de precios a lo largo del umbral de tiempo sobre los resultados hoteleros es un factor importante que los revenue managers deben diferenciar en el proceso de toma de decisiones; ya que no es lo mismo una variación de precios provocada por cambios de demanda a lo largo del horizonte temporal de reservas, que pueden variar diariamente, que cambios de precios producidos por obras sobre los atributos físicos del hotel, que solo pueden variar a largo plazo. En una primera fase, la actual tesis presenta un modelo de función de demanda enfocado al sector de hoteles vacacionales, que mide la demanda online así como van cambiando las variables precio y momento de la reserva. La primera tanda de resultados muestra que hoteles situados en el mismo destino turístico, que pertenecen a la misma cadena hotelera, son capaces de exhibir comportamientos de la demanda totalmente diferenciados –por lo que se refiere a la elasticidad precio de la demanda– a lo largo de las diferentes temporadas y momentos de reserva. Mientras que en una segunda tanda de resultados, procedentes de siete hoteles vacacionales situados en tres destinos españoles y que también pertenecen a la misma cadena hotelera, destaca que presentan demandas elásticas durante la mayoría de periodos de la temporada alta, pero se detecta que algunos factores de los hoteles pueden reducir las elasticidades –tales como la remodelación del hotel, la oferta de instalaciones y servicios adicionales, los segmentos de clientes que viajan en pareja y/o consumen media pensión, la mayor proporción de turistas alemanes o la menor proporción de competidores locales. Y en una segunda fase, se adaptan las funciones de demanda a modelos dinámicos determinísticos y estocásticos que permiten la fijación de precios que maximizan los ingresos de dos hoteles vacacionales situados en un mismo destino turístico –las estimaciones estocásticas son normalmente más similares a los últimos datos observados, mientras que los modelos determinísticos normalmente producen estimaciones más similares a los valores medios del conjunto de datos. Los resultados muestran que los precios óptimos se ven afectados por la distribución de las elasticidades a lo largo del horizonte temporal de reservas, la variabilidad natural de la demanda, la estacionalidad y los atributos propios del hotel –tales como el número de habitaciones disponibles, la localización del hotel y el perfil de sus turistas. En conclusión, hoteles situados en un mismo destino turístico normalmente presentan políticas parecidas de fijación de precios, debido a que en cadenas hoteleras es normalmente la misma persona quien gestiona hoteles situados cerca. Mientras que los resultados resaltan que hoteles situados en el mismo destino deberían seguir políticas de precios individualizadas, más enfocadas a los atributos específicos del hotel y a las características de sus clientes.

I. Introduction

1. Motivation of the Thesis

Last years the e-commerce has transformed the way customers and companies behave, a process that has been especially relevant in the tourism industry. The marketplace built with the internet allows the tourists to obtain information, to check availabilities and prices, and to book many tourist products, while at the same time most of the tourist products can be advertised, can compete and can be directly sold in internet. The information generated and collected via internet and the way it is used represents a key issue in the revenue determination of the tourism companies. Thus, the way the tourism product is commercialized and sold has significantly transformed the tourism companies. This transformation process has been especially relevant in the sun and beach destinations, particularly for the loss of power of tour operators, the traditional intermediaries which exerted a high control on tourists, in the origin market, and on the resort hotel segment, of many destinations (Aguiló et al., 2003). This process represents a new opportunity for hotels to carry out a direct marketing with tourists and a possibility of increasing revenues with this new marketplace using new business strategies.

The hotel sector presents some specific characteristics, such as perishability, capacity limitations and seasonality, which make the pricing and occupancy management key factors in revenue determination (Anderson and Xie, 2010). Precisely, the Revenue Management (RM) discipline deals with these issues, since it can be defined 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 (Legohérel et al., 2013; Ivanov and Zhechev, 2012; Ivanov, 2014; Smith et al., 1992). In this sense, the RM has helped many service companies to increase their profits, as they can sell homogeneous products at different prices to different types of customers (Cross et al., 2011). The perishability of the hotel product, in conjunction with the capacity limitations of hotel establishments as well as seasonality, place the demand management as a crucial factor in the revenue maximization process (Coenders et al., 2003; Ivanov & Zhechev, 2012).

Over the last four decades the RM techniques have significantly evolved and have proved to be effective, first in the airline sector and later in the hotel sector and other services sectors. The beginning of the RM is placed with the 1978's airline deregulation and liberalization that lead to the subsequent significant increase of profits, throughout the management of occupancy and setting discounted fares, which fostered the emergence of the low-cost airlines (Cross et al., 2011; Pachon et al., 2007; Smith et al., 2001; Talluri and van Ryzin, 2005; Vinod et al. 2009). The RM techniques were introduced in the hotel sector in the mid-80's, the first hotel company adopting RM techniques was Marriott International, which invested in a RM system development that made demand forecasts and recommendations in the assignation of capacity (Cross et al., 2009; Cross et al., 2011). Ten years later the RM system included price optimization techniques and allowed an increase of 150-200 million dollars in Marriott's annual profits (Cross et al., 2011). However, after the hotel occupancy dropped due to the 9/11 events, as well as the transformation effect from the information and communication technologies, the price optimization processes moved from a product to a consumer orientation and allowed the introduction of higher levels

of price transparency (Cross et al., 2009; Koushik et al., 2012). Thus, the optimization processes in demand forecasts and inventory management have evolved towards a greater capacity for segmenting the demand, through the improvement of the customer behavior determination, and from a sector's to an individual hotel level estimation (Hormby et al., 2010). The latter RM techniques developed in the hotel sector include the demand behavior segmentation and price elasticity modeling in the hotel room price optimization process (Noone, 2016), for instance, in Marriot International these price optimization techniques represented a 1.1-1.8% revenue increase after their implementation (Hormby et al., 2010); while Intercontinental Hotel Group increased the revenue per available room by a 2.7% with a new price optimization system (Cross et al., 2011).

Therefore, customer segmentation represents a basic tool within the RM, which is governed by the demand heterogeneity and seasonal fluctuations. The segmentation allows the customer aggrupation according to its price sensitivity and interrelations among the different segments. The high levels of competitiveness that the literature usually confers to the hotel sector place the market segmentation as a basic instrument for the hotel survival and its success in the market (Dolnicar, 2002). In the hotel sector the most common way to segment customers is to set different prices according to the different booking behaviors (Hanks et al., 2002). The price differentiation allows the hotel to focus on different customers segments, which are aligned with their willingness to pay, product characteristics, and customer characteristics (El Haddad et al., 2008; Ivanov, 2014).

The time threshold perspectives also exert a high level of influence in the RM analysis (Ivanov, 2014):

1. The operational or short-run analysis, which gets actualized daily or weekly, and uses competitors' prices and demand data evolution. As the capacity is fixed, the revenue manager can adjust the demand at times when the forecasted occupancy differs from the actual demand through price variations (Avinal, 2004; Lee, 2016).
2. The tactical or medium-run analysis, which tries to measure the seasonal demand, seasonal trends, and evaluates the efficiency of the different reservation systems; the tactical analysis represents assets or demand behaviors that cannot be altered at the short-run.
3. The strategic or long-run analysis, which focuses on the yearly metrics such as volume of demand, spending, and the customer structure. This analysis involves factors such as hotel physical aspects, and strategic factors that cannot be altered at the short and medium-run. Usually the longer-run perspectives of market segmentations and price decisions are not considered frequently (Talluri and van Ryzin, 2005), but the strategic perspective becomes very important in the hotel heterogeneity determination.

The strongest instrument for the hotel sector positioning is the price variable (Ivanov, 2014; Ivanov and Zhechev, 2011). The characteristics of the tourism industry place the pricing as a basic tool in the revenue maximization process (Cheng et al., 2011; El Haddad et al., 2008). Pricing is considered the most flexible and easily adjustable marketing strategy in the dynamic environment of the hotel sector (Hung et al., 2010).

Consequently, the price discrimination focus on the price variation according to the type of guest, as opposed to the cost of the service, is based on the different behaviors and price sensitivities of each market segment.

There are two main sources that explain the price changes within the same hotel establishment and/or among different hotels. Firstly, the hotel internal segmentation, which is directly controlled and managed by the hotel managers; in fact, several factors explain the hotel price variability and allow internal segmentations, such as:

- Booking date (Schütze, 2008): The reason for limiting the number of rooms to be sold at any moment on the booking horizon is based on the expectation that they will be sold in the future to a more profitable demand (Aziz et al., 2011).
- Rate fences: Fences are restrictions or rational rules that lead to tourist self-segmentation, depending on their willingness to pay, behavior or needs (Hanks et al., 2002; Kim et al., 2004; Kimes and Wirtz, 2003; Liu et al., 2002).
- Tourist types: Hotels can offer multiple prices for what is essentially the same room in order to serve different tourist segments with a different willingness to pay. This allows the hotel to maximize its revenue and reduce its consumer surplus (Kimes and Wirtz, 2003).
- Seasonality: The prices of a room booked in the high season are expected to be much higher than those booked in the low season (Aguiló et al., 2001; Coenders et al., 2003; Narangajavana et. al., 2014).

And secondly, the hotel external segmentation is not directly controlled by the RM department, at least in the short-run, and includes issues such as the hotel attributes, the customers' perception of these attributes, and the destination context, i.e., hotel differential pricing. One of the best ways for measuring these issues is to determine a hedonic pricing model, but this type of models do not consider the consumer behavior and their willingness to pay (Aguiló et al., 2001), so the estimation of demand functions is a direct and easy way for determining the customer behavior.

2. Theoretical Framework

A direct approach for measuring market reactions to price variations is to estimate own-price elasticities of demand, through a demand function (Desiraju and Shugan, 1999; Lee, 2011; Shy, 2008). The rooms' prices set along the booking horizon that allows the hotel revenue maximization is called optimal dynamic pricing, these are the most extended models used in the hotel revenue maximization (Bandinelli, 2000). Mainly, there are two types of optimal dynamic approaches in the literature; the first type is the deterministic model which is used to discriminate prices considering the different segments behaviors across the booking horizon that allows the revenue maximization (Aziz et al., 2011; Guadix et al., 2010; Lee, 2011). The second type is the stochastic dynamic model which segments the demand into different classes; every class is interrelated with the rest of segments and the objective is the determination of the global market responses to price variations that allows the revenue maximization

(Jacobs et al., 2010; Pachon et al., 2007; Ratliff et al., 2008; Suzuki et al., 2001; Talluri & Ryzing, 2004; Vinod et al., 2009).

3. Aim of the Thesis

The general aim of the thesis is to establish the best way of determining the customers behaviour, which allows their segmentation, and to find out the optimal pricing methods that allow revenue maximization in the resort hotel sector. The availability of real hotel information has allowed the empirical testing of the theoretical methodology set in the thesis, as well as the comparison and discussion of the different results in terms of elasticities and prices that maximize revenues. Thus, the main objectives of the thesis are:

1. To determine and classify the main sources of hotel price variation, customer segmentation and price optimization methods and RM techniques in the hotel sector described in tourism literature, and to summarize current trends in hotel pricing research and hotel RM literature.
2. To develop a demand function for the online transient demand for resort hotels that allows the determination of the different booking horizon customers' sensitivities (own-price elasticity), the different seasonal segments, and the different customer behaviors among hotel establishments. The own-price elasticity values enable the analysis and comparison of the customer behavior diversity.
3. To apply the demand functions in the development of optimal dynamic pricing models that allow the revenue maximization for resort hotels. Hence, the aim is to adapt and apply the two widespread revenue maximization models used in the literature to the hotel resort segment, i.e., the deterministic and stochastic dynamic pricing models; as well as to provide an empirical comparison of both models for the online transient segment.
4. To estimate and compare the different own-price elasticity values and optimal prices for the online transient demand of hotels with different attributes/factors and in different hotels located in different resort destinations across the booking horizons and seasons. It is important to explore hotel location, specific hotel attributes, and customer characteristics that can explain the differences in elasticities between the different hotels and tourism destinations.

The structure of the thesis is organized as follows. After the introduction, chapter 1 presents a critical literature review about revenue management and price optimization techniques in the hotel sector. Chapter 2 presents an online hotel demand function model and it is empirically implemented in two Majorcan resort hotels. Chapter 3 presents two optimal pricing models for online hotel demand which are implemented to the same hotels of chapter 2. Chapter 4 implements and compares the demand model of chapter 2 to seven different Spanish resort hotels located in different destinations. Conclusions highlight the main conclusions of every chapter and the general conclusions of the thesis. Finally, the annex section empirically implements

one of the optimal models described in chapter 3 to the seven hotels analyzed in chapter 4.

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II. Empirical Chapters

Chapter 1. Revenue Management and Price Optimization Techniques in the Hotel Sector: A Critical Literature Review

Abstract

Pricing and revenue management (RM) techniques have become a popular field of research in hotel management literature. The sector's background framework and evolution, and the widespread use of new technologies have allowed a customer-oriented approach to be taken to pricing and the development of RM tools, while also contributing to better processes in hotel management performance at individual hotel level. Thus, price optimization (PO) methods that seek to maximize hotel revenue are based on inventory scarcity, customer segmentation and pricing. In the hotel sector, as in the airline industry, different pricing policies have a greater impact than competition measurement effects. This is mainly as differentiation strategies and specific policies at hotels can reduce the pressure of a competitive environment. The main contributions of the paper are the presentation, description and classification of the principal revenue management and price optimization techniques in hotel sector literature.

Keywords

Price elasticity of demand, dynamic pricing, customer choice models, hotel revenue management, seasonality, booking horizon

1.1 Introduction

Over the last two decades, pricing and revenue management (RM) techniques have become a popular field of research in tourism literature. Cross et al. (2011) point out that RM techniques have contributed to improved profits at many companies, without them having to offer different products or sell to different customers. Ivanov (2014) and Ivanov and Zhechev (2012) place the price variable as the strongest instrument of hotel market positioning. Several questions arise regarding pricing and RM techniques, mainly: what are these pricing and RM techniques? What have been the main motivations that have enabled the RM evolution? What are the current trends of research? This paper presents a comprehensive review on revenue management and price optimization (PO) methods in the hotel sector in an attempt to answer to these questions.

1.1.1 Aims of the Article

Hotel pricing can be based on different factors and there are many articles analysing this topic from different perspectives in the literature. In this sense, this paper brings together most hotel pricing literature in order to describe the current situation of price differentiation and see which direction it will take in the near future.

Given the characteristics of the tourism industry and the relevance of demand, pricing is a basic tool in the revenue maximization process (Cheng et al., 2011; El Haddad et al., 2008). Price variations allow hotels to focus on different customers segments, which are aligned with their willingness to pay, product characteristics and customer characteristics (El Haddad et al., 2008; Ivanov, 2014). Due to certain features of the hotel sector (such as perishability, capacity limitations and seasonality), occupancy and demand management play a key role in determining revenue (Avinal, 2004). The presence of competitors and substitute products, higher levels of demand variability and the levels of uncertainty regarding future demand also influence pricing decisions and demand management (Talluri and Van Ryzin, 2005). Hence, an awareness of the main PO models used in the hotel sector and the key factors that affect price variability is fundamental in hotel RM.

Ivanov (2014) differentiates three dimensions in the RM time horizon analysis: (1) operational or short-run analysis, which is updated daily or weekly, and uses competitors' prices and demand; (2) tactical or medium-run analysis, which tries to measure seasonal demand, seasonal trends and evaluates the efficiency of the different reservation systems; and (3) strategic or long-run analysis, which focuses on yearly metrics such as demand volume, spending and customer structure.

As capacity is fixed at a shorter-term perspective through price variations, a revenue manager can adjust demand at times when forecast occupancy differs from actual demand (Avinal, 2004; Lee, 2016). Meanwhile, the medium and long-term price differentiations take a more tactical and strategic perspective, and involve factors such as knowledge of demand behaviour and assets that cannot be altered in the short-term. Talluri and Van Ryzin (2005) point out that the longer-run perspectives of market segmentations and price decisions are not frequently taken into consideration. However, the strategic perspective becomes very important in comparisons between hotel establishments. Kim et al. (2016) demonstrate that idiosyncratic price movements along the booking horizon lead to hotel room revenue increases in the short-term, but to revenue reductions in the long-term.

Therefore, the availability of information on hotel demand is a key factor in RM development (Avinal, 2004). In this sense, Information and Communication Technologies (ICTs) have had an enormous effect on the transformation of the hotel sector. Large amounts of data and the availability of real-time information have enabled PO processes to be improved and have led the sector to move towards more customer-oriented pricing processes. Indeed, many benchmark hotel data companies have appeared recently, supplying hotel metrics that allow revenue improvement and better customer segmentation. These companies use powerful systems that are able to process data based on the hotel and on the competitive environment (e.g. STRglobal).

The aim of this review is two-fold: firstly, to determine and classify the main sources of differential hotel pricing and the main methods for PO shown in the literature and, secondly, to summarize and situate current trends in hotel pricing, hotel customer segmentation and RM research.

1.1.2 Background Framework to the Sector

RM is widely defined in the 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 (Legohérel et al., 2013; Ivanov and Zhechev, 2012; Ivanov, 2014; Smith et al., 1992). In terms of the applicability of time horizons for hotel RM, short-run RM depends on three factors (Legohérel et al., 2013; Ivanov and Zhechev, 2012; Ivanov, 2014): (1) the possibility of advance bookings; (2) the ability to manage price variations across the booking horizon; and (3) the possibility of segmenting demand into homogeneous groups with different price elasticities. In contrast, the applicability of medium and long-run RM is dependent on factors like physical aspects, strategic factors or knowledge about demand behaviour.

Given the characteristics of the hotel sector, pricing, occupancy and demand variables represent key factors in determining hotel revenue (Anderson and Xie, 2010), especially in the short-term. Thus, demand heterogeneity, as well as its seasonal fluctuations, lead to the customer segmentation—one of the main RM tools. In this vein, Talluri and Van Ryzin (2005) position the heterogeneous nature of demand under three measurements: (1) the diversity of the marketed product; (2) the diversity of customers served; and (3) time. Dolnicar (2002) points out that in a competitive market like the hotel sector, market segmentation plays an essential role in success. Nevertheless, among the various RM tools, pricing is considered to be the most flexible and easily adjustable in the dynamic environment of the hotel sector (Hung et al., 2010).

1.1.3. Methodology

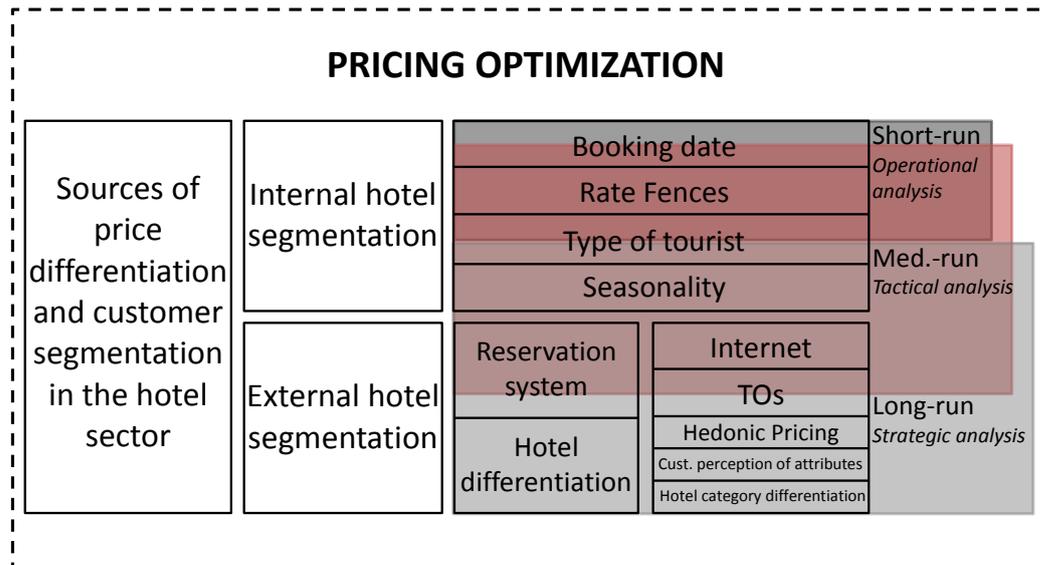
In order to identify studies for review, the authors firstly undertook a review of general tourism RM and pricing books, such as Talluri and Van Ryzin (2005) and Shy (2008), to then move onto a literature review of specific articles in the social science citation index and Scopus that place RM and pricing techniques within hotel literature, such as Cross et al. (2009; 2011) and Ivanov and Zhechev (2012), among others.

Searches were also made on the Scopus and Elsevier databases, and Google Scholar application. The keywords used related to the hotel sector and to the topic of this paper, such as RM, pricing, price elasticity of demand, dynamic pricing (DP) and customer choice. The last search was made at the beginning of May 2017. Only papers published in English have been considered in the sample, which totals 152 articles and books. Subsequently, each contribution was analysed and, according to its contents, classified into one of the 10 streams described in the following section.

1.1.4. Structure of the Article

Several factors can cause price variability within the same hotel and/or among hotels. These factors are sources of price differentiation, customer segmentation and pricing optimization in the hotel sector. *Figure 1* summarizes these factors:

Figure 1. Sources of price variability and demand segmentation in the hotel sector.



Source: Prepared by the author

Given the different factors that affect price variability collected in *Figure 1*, and following on after the introduction, this paper is structured as follows. The first section describes customer segmentation in the hotel sector. The second section analyses different PO methodologies described in the relevant literature. Finally, the paper concludes with a summary of future fields of research.

1.2. Customer Segmentation in the Hotel Sector

Segmentation is the process where customers are grouped according to the needs and demand requirements they share (Ivanov, 2014). All of these customer groups share similar responses to price and marketing variables, and the objective is to be aware of who these customers are, how they buy, what they value and their willingness to pay (Talluri and Van Ryzin, 2005). The progress in customer segmentation and understanding them is a basic step in customer satisfaction (Zhang and Bell, 2012). Rondan-Cataluña and Rosa-Diaz (2014) indicate that segmentation in tourism is challenging as every tourism location may have different features, external factors and past marketing efforts. Png (2013) highlights three types of price discrimination: (1) complete price discrimination, where the seller knows all individual buyer curves; (2) direct segment discrimination, where the seller directly discriminates based on buyer attributes and where it can prevent migration among buyer segments; and (3) indirect segment discrimination, where the seller uses the product attributes to discriminate among buyer segments. Wu et al. (2012) define customer segmentation in the hotel sector as the strategy of changing prices over time, across customers and across situations. Nonetheless, the literature on hotel pricing and customer segmentation is very fragmented and, at times, each segmentation type refers to different types of pricing management or different pricing time thresholds. Thus, our classification in this study will differentiate between internal and external RM segmentation, and the time horizon dimensions of each segmentation type.

1.2.1. Internal Segmentation

This segmentation is directly controlled and managed by the RM department. When making pricing decisions, revenue managers consider factors such as the economic market conditions, events or seasonality (Kim et al., 2016).

Booking Dates. Hotels can set different room prices according to tourist booking behaviour (Hanks et al., 2002). This is the most common form of customer segmentation in RM (Schütze, 2008). At some points across the booking horizon, the hotel can limit the number of rooms on sale in order to keep them back for later moments with more profitable demand (Aziz et al., 2011). The main reason for keeping rooms back is limited hotel capacity (Bandinelli, 2000). In hotel RM approaches, booking dates use to take a short and medium-run perspective.

Aziz et al. (2011), and Desiraju and Shugan (1999) point out that low-price tourist demand occurs during the early booking stages, while the price increases as the reservation time gets closer to the date of stay. Selling too many rooms at a demand with a low-price elasticity can lead to a potential loss of revenue due to the lack of available rooms for later demand. On the other hand, keeping too many rooms back for demand with high price elasticity can result in too many unbooked rooms. Different market segments might have different reservation patterns across the booking horizon (Bandinelli, 2000; Lee, 2011). For example, airport hotels normally have short booking horizons, while resort hotels display the longest ones. Nevertheless, Lee (2011) and Lee et al. (2011) find that hotel rates, particularly rates for the individual segment, do not increase as the day of arrival approaches. Abrate et al. (2012) point out that booking horizon pricing strategies depend on customer value and patience. Wu et al. (2012) find that time horizon price discrimination does not affect customers' feelings of fairness as customers who have to pay a higher price are unable to change their behaviour. Lee (2016) indicates that as the date of stay gets closer, the perishability of the product can increase pressure on the hotel manager to set discounts against the risk of losing revenue from unsold capacity. Kim et al. (2009) point out that hotel chains do not need to give big early booking discounts. Instead, in the early stages, they use small price reductions to maintain similar occupancies to historical levels and, as the date of stay approaches, they offer larger discounts due to the surplus supply. Whatever the case, customer willingness to pay varies as the arrival date draws closer (Cross et al., 2009), and the right combination of tourists with different booking behaviours will help to maximize revenue (El Gayar et al., 2011).

Rate Fences. Rate fences represent the rules used to segment demand and justify differential pricing (Liu et al., 2014). Usually these fences include consumption characteristics (refundability on advance reservations, minimum length of stay, group size), product characteristics (room location, type, board), membership of certain organizations, customer loyalty and booking time (Ivanov, 2014). The same hotel may offer different kinds of rooms and/or levels of service, or different reservation conditions that lead to customer self-segmentation (Coenders et al., 2003; Ivanov and Zhechev, 2012; Narangajavana et. al., 2014); meanwhile, other fences include insuperable barriers the customer has to meet such as length of stay or group size.

Ivanov (2014), and Zhang and Bell (2012) consider the fences a tool that allows market segmentation and limits migration from one segment to another, enabling rational customer behaviour adjustment to hotel objectives. Fences can be defined as restrictions or rational rules that lead to tourist self-segmentation, depending on their willingness to pay, behaviour or needs (Hanks et al., 2002; Kim et al., 2004; Kimes and Wirtz, 2003; Liu et al., 2002). Kim et al. (2004) point out that the discriminatory pricing system of fences must be understood by customers in order to minimize the number of tourists who fail to understand them and book elsewhere. The rate fences are usually applied in the short and medium-term.

Ng (2009) demonstrates that refundability can be an optimal strategy for advanced bookings, as it allows companies to raise prices and increase the amount sold during the advanced booking period, while it also acts as a form of insurance for consumers. Liu et al. (2014) do not find significant differences in the preference for hotel bookings between Chinese and Western tourists in terms of advance requirements and refundability, merely noting differences regarding policy changes. Lee (2011) does not find significant differences in the booking behaviours of a segment with advanced purchase requirements and another with refundability. Wu et al. (2012) find that specific member discounts do not negatively affect feeling of fairness among other customers. Noone (2016) indicates that hotel price transparency and the need to boost demand have contributed to the reduction in rate fencing. Yimaz et al. (2016) study standby upgrade reservations, which represents a complementary service or service improvement that is only charged to the customer if it is available on the arrival date. They find that these types of reservations are more suitable for non-repeat customers. Standby upgrade reservations represent an additional way of increasing hotel revenue, as the hotel is able to set a better price discrimination and avoid overbookings in certain types of rooms.

Tourist Types . Cross et al. (2011) state that tourist perceptions of the value of a hotel product should be understood and aligned with the product characteristics and prices for each segment, since each segment has different price sensitivities (Desiraju and Shugan, 1999). Hanks et al. (2002) point out that tourism consumption decisions will be based on the specific date of stay, location and purpose of the trip. In terms of RM time analysis, sales can be limited at certain moments of the booking timeline for a specific segment due to hotel capacity limitations (short-run), and the historical data and RM experience can indicate how many rooms have to be devoted to each segment (medium and long-run).

The most common form of tourist differentiation is to distinguish between leisure and business travel (Gallego and Van Ryzin, 1994). Ivanov (2014) differentiates between price sensitivity in the leisure segment and in the business segment, where the business segment is generally more inelastic and can afford to pay higher prices. More specifically, the leisure segment is more heavily focused on weekend periods and the business segment on weekdays (Abrate et al., 2012; Balaguer and Pernías, 2013; Lee et al., 2011), while price discounts are usually given for weekends (Hanks et al., 2002) and the level of patience in the business segment tends to be lower (Abrate et al., 2012). Yavas and Babakus (2005) state that the needs of both groups differ in terms of hotel

attributes, since one segment may require specific facilities that are not needed by the other. Dolnicar (2002) stresses the importance of attributes such as location, reputation and price for the business sector.

Guadix et al. (2010) point out that different strategies are needed for group parties staying at hotels, as opposed to individuals. Groups usually pay more and have a lower probability of being no-shows. Maier and Johanson (2013) investigate the convention/group and individual traveller segments. They conclude that more efforts should be made to identify and manage the convention segment.

Lee (2011) differentiates three hotel segments: groups who have assigned rooms, for example, demand for a conference; negotiated demand, mainly corporate guests or big travel agencies, and individual demand. The RM department is only able to affect the individual segment.

Finally, Chu and Choi (2000) state that the identification of different segment needs, desires and expectations is crucial in developing better marketing strategies and in achieving competitive advantages.

Seasonality. Seasonality usually arises as a result of natural factors associated with temperature, the weather and climate, or institutional factors associated with school holidays, religious festivals and other special events (Lim and Chan, 2009). This phenomenon can lead to high fluctuations in demand and different prices can be found for the same product (Narangajavana et al., 2014). The seasonal segmentation can take the medium and long-term dimensions in RM time analysis as, in order to carry out this segmentation, information on previous seasons is required.

Taking seasonality as a basis, Coenders et al. (2003) analyse resort hotel prices and find that prices can double or more than double during peak season, as opposed to the low season. During peak demand periods, hotels offer high-price rooms, while during low-demand periods discounts are made on room prices in order to boost demand (Collins and Parsa, 2006). Gallego and Van Ryzin (1994) and Pan (2007) point out that high- and low-season optimal room prices are significantly affected by market demand fluctuations. Juaneda et al. (2011) also find that low-season prices double during the peak season at Mediterranean resort hotels. Their results show slight seasonal differences between hotels and apartments. In the urban hotel segment, even though it is generally accepted in the literature that demand is stronger on weekdays than at weekends, the findings of Lee (2011) and Lee et al. (2011) indicate that there are no significant differences between the demand of each. Cross et al. (2009) highlight the fact that in tourist booking behaviour, it is sometimes difficult to isolate seasonal effects from remaining price effects.

1.2.2. External Segmentation

These are factors that can be used to segment customers that are not directly controlled by the RM department, at least in the short-term. Sometimes segmentation comes from other variables such as product attributes or marketing variables (Talluri and Van Ryzin, 2005).

Reservation Systems . Hotels use a diversity of reservations systems or distribution channels. The two main reservation systems can be divided into direct hotel sales or via travel agencies, and both types of channels can sell hotel products on- or offline. Therefore, this article will differentiate between traditional intermediaries that sell offline and the internet—the new era of online distribution channels. Most distribution channels are unable to be changed in the short-run, as they require specific software development or contract agreements with intermediaries that prevent immediate modification. Pappa (2014) points out that tourists with greater knowledge and use of ICT are usually younger and more educated, while elder and less educated tourists usually depend on traditional reservation systems and ways of advertising. Kim et al. (2014) find a positive relationship between price dispersion and hotel performance in the offline channel, while this relationship is negative in the online channel. The main reasons are the higher degree of price transparency and the regularity in price changes in the online channel, which make a contrasting pricing policy of both channels a source for hotel performance.

Traditional Intermediaries: Intermediaries have the power to exert a direct influence on competitiveness in the industry and influence consumer behaviour (Bastakis et al., 2004). These companies play the roles of representation, design and promotion of tourism packages, advertisers and promoters (García-Falcón and Medina-Muñoz, 1999).

The role of leading tour operators (TO) is to act as a bridge between tourism supply and demand and to market these packages to different tourist segments (Huang et al., 2010). The existence of the TO package is justified by the existence of production and transaction cost savings, the achievement of economies of scale and scope (Chen et al., 2015-a; Kim et al., 2009), and the generation of demand and segmentation (Kim et al., 2009).

TO packages can help to reduce uncertainties in tourist destinations (Chen et al., 2015-a; Zang et al., 2009), as they may lead to tourism development there, due to the control exerted by origin markets (Huang et al., 2010). High competition among destinations makes prices and package holiday differentiation key factors in competitiveness (Aguiló et al., 2001).

The negotiation between TOs and hotels usually takes place one year in advance and hotel revenue mainly depends on the level of occupancy offered by the TO (Aguiló et al., 2003). Hence, hotels contractually transfer part of their business risk to the TO in order to improve their planning capacity and visibility in the origin market (Bastakis et al., 2004).

In the literature on TO package holidays, Chen et al. (2015-a) find an inverse relationship between tourist satisfaction and the market share of package holidays. The price structure and factors that differentiate each package holiday have direct implications on tourist assessment of TO products. Aguiló et al. (2001) claim that by controlling these factors, TOs can pinpoint different market segments. Aguiló et al.

(2003) find that the hotel demand curve in the Balearic Islands is very elastic, due to TO market power. The latter are price sensitive, and so hotel profits are dependent on the total number of tourists brought to hotels by TOs. Customer loyalty has a huge impact on TO products, as TOs have the power to persuade customers regarding which destination to visit (Aguiló et al., 2003).

The Internet: Canina et al. (2005) indicate that travel agencies have been replaced by the internet as a primary source for tourist information. The development of ICTs has had an enormous effect on hotel sector pricing strategies. New technologies make prices more transparent (Anderson and Xie, 2010). The increase in online sales in the travel market leads to a more competitive marketplace because tourists have become more price-sensitive and price-conscious (Kim et al., 2009). Demirciftci et al. (2010) point out that the most important factor in purchasing a trip online is the savings; therefore, the commoditization of the hotel product has increased pricing, while the sector's branding has become less important.

The internet has transformed the way in which companies and tourists behave, especially in terms of marketing and distribution (Buhalis and Law, 2008). It has led to a disintermediation process (Zare and Chukwunonso, 2015) and it fulfils distribution, transaction, and communication functions at a lower cost than conventional channels (Tse, 2003). Kim et al. (2009) find that the price of travel packages sold by online travel agents is lower than prices marketed by individual online service providers. The internet also enables tourists to identify, customize and purchase tourism products that meet their needs. It has created a new marketplace where tourism suppliers can contact customers directly (Buhalis and O'Connor, 2005). The swift identification of consumer needs, interaction with consumers, the supply of customized up-to-date tourism products, the availability of services and their customization, and the contribution to the globalization of the tourist industry are key ingredients in the internet's success (Buhalis and Law, 2008; Buhalis and O'Connor, 2005). Thanks to ICTs, market competition conditions, entry barriers and distribution channels have changed (Buhalis and Law, 2008; Buhalis and O'Connor, 2005).

Abrate et al. (2012) point out that hotels' own websites have higher price levels than other online distributors. However, direct hotel sales through their own websites may reduce transaction costs (Varini et al., 2003). Compared to traditional reservation systems, the internet has typically presented higher price dispersion and this has implications for customer perception of price fairness (Demirciftci et al., 2010). In terms of room rate parity, they find no relevant differences in prices shown in direct hotel sales and those on indirect channels; however, they do find significant differences in prices when both channels are considered independently of one other. The study also refutes the lowest price guarantee marketed by certain hotel chains, showing that it is a mere marketing tool used to increase direct sales. In turn, Ivanov and Piddubna (2016) detect a lack of rate parity among the online channels of accommodation establishments in Kiev, specifically the prices on company websites were lower than at online travel agencies. Du et al. (2016) find that hotels using market segmentation, collaborating with online intermediaries, have lower levels of profitability and occupancies compared to hotels that solely use the market

segmentation. Guo et al. (2013) find that the integration of direct hotel and online intermediary bookings as a single player is the optimal scenario. Similarly, Guo et al. (2014) highlight that the cooperation between hotel website and online intermediary bookings leads to 35% higher profits compared to the competitive scenario between the two distribution channels. They also emphasise that this coordination increases when the fee paid to the online intermediaries includes all online bookings. Ling et al. (2014) show that the optimal commission is directly related to hotel occupancy or the number of hotels working with the online intermediary, while the optimal commission is inversely related to the number of customers or potential customers the intermediary has. The higher number of available rooms determines a better position on the online intermediary website. Finally, hotels with lower occupancies are more likely to work with an online intermediary.

Hotel Differentiation. Hotel attributes and categories, and the way the customer perceives these attributes, are further basic issues in customer segmentation and pricing processes. However, all these hotel features cannot be changed in the short and medium-term.

Hedonic Pricing (HP). According to hedonic price theory, the value of hotel attributes and their characteristics are unobservable since they are not individually sold (De Oliveira Santos, 2016; Espinet et al., 2003), and so HP models try to capture hotel price heterogeneity. Hotels with many desirable attributes will be more expensive than others (Thrane, 2007). However, this heterogeneity is attributable to the market's possible segmentation and the model does not allow for the identification of consumers' willingness to pay or the elasticity of demand (Aguiló et al., 2001). HP literature identifying hotel attributes that affect hotel data includes: Abrate et al. (2011), Abrate and Viglia (2016), Aguiló et al. (2001), Aguiló et al. (2003), Balaguer and Pernías (2013), Coenders et al. (2003), De la Peña et al. (2016), Espinet et al. (2003), Ivanov and Piddubna (2016), Juaneda et al. (2011), Latinopoulos (2018), Lee and Jang (2011), Monty and Skidmore (2003), Papatheodorou (2002), Soler and Gémar (2016), Thrane (2005, 2007), Tochaiwat and Likitanupak (2017), White and Milligan (2002) and Yang et al. (2016). Among this literature, a hotel's star category is the most common attribute affecting price levels, but lately online rating has become increasingly important; another popular factor is hotel location, or distance to the beach or city centre; booking date; reservation characteristics; tourist profile; seasonality; TO or online travel agency; room facilities; hotel characteristics/facilities; type of hotel; competitive, economic and/or environmental context, and temperatures.

Coenders et al. (2003) consider seasonality in conjunction with other hotel attributes. They find that three-star hotels display the highest seasonal effects and four-star hotels the lowest, while the attributes that display the biggest price difference in the peak season are proximity to a beach, room amenities and parking facilities. Meanwhile, White and Milligan (2002) find that price variations in the attributes remain constant when the winter and summer seasons are compared. Juaneda et al. (2011) compare the effect of prices on hotels and apartments located in different destinations at different seasonal times. In terms of the actual location, tourists staying at hotels are found to perceive more differences in quality among the different

destinations. Both types of accommodation display similar seasonal effects. Abrate and Viglia (2016) analyse three types of variables that affect prices: tangible hotel attributes, the reputation and contextual variables (including the booking time and seasonal factors, free cancellation fences and the presence of competitors). The findings are as follows: tangible attributes have a possible correlation with the star rating; online reviews are a suitable alternative for star ratings; prices tend to drop slightly across the booking horizon; no statistical differences are found between weekday and weekend prices; the free cancellation option has a positive effect on prices, and an increase in the number of local competitors has a negative impact on prices. Ivanov and Piddubna (2016) detect that prices on Booking.com are more dynamic compared to those on hotels' own websites and Expedia.com. They also find that the availability of parking at the hotel only has a positive influence on price on Booking.com. De la Peña et al. (2016) link hotel innovation and internationalization to hotel attributes. Yang et al. (2016) study the effect of market accessibility (in terms of travel costs) on Caribbean hotel prices. They show that high travel costs (market inaccessibility: low season) lead to low hotel prices, while these low prices can be mitigated by a good reputation on TripAdvisor.com or by belonging to a hotel chain.

Using a quantile regression analysis, Hung et al. (2010) find that the main attributes responsible for determining hotel room prices are hotel size and age, market conditions and the number of housekeeping staff per room. However, the hotel age and market conditions are only significant in the case of high-price hotels, while hotel size and the number of housekeeping staff per room are not significant for low-price hotels. Meanwhile, Corgel et al. (2015) highlight that 80% of price variations for hotel attributes are determined by the property's characteristics, the city market net rent and local economic variables, considering all these variables together in a single model.

Consumer Hotel Valuation. Understanding customer assessments of hotel attributes is fundamental, since they affect customer satisfaction and behaviour (Kang et al., 2004). Chu and Choi (2000) compare the business and leisure segment perceptions of hotel selection factors and find that both have the same perception of attributes such as quality business, hotel facilities, value, the room and front desk, food and recreation, and security. Tsaour and Tzeng (1996) note that the main hotel decision factors are reputation, image and good transport links. Danziger et al. (2006) find that star ratings and the price factor are the most important pieces of information for tourists, and brand information is also important when the star rating is not available. The results obtained by Shieh et al. (2014) show that the most attractive attributes are hotel size and age, as well as the proximity to the nearest international airport. They also find that the perception of the attributes varies by nationality. Dolnicar (2002) shows that the most highly appreciated hotel attributes are cleanliness, friendliness and good food, while the staff is a source of dissatisfaction. She finds major differences depending on the category of hotel where the business segment stays. Kang et al. (2004) explore what factors influence customer satisfaction at two types of Japanese accommodation centres: hotels and traditional Japanese inns. The most important factors influenced by the type of accommodation are physical aspects, creativeness, unexpected service and encounter performance. Lin and Huang (2015) detect that the RM knowledge level is positively related to customer loyalty, and a higher level of

loyalty is found for customers perceiving a high level of pricing fairness. Heo and Hyun (2015) study the effect of customer willingness to pay from a demand side caused by the supply of room amenities in the luxury hotel segment. They show that Wi-Fi is the most important attribute, followed by the availability of luxury brand room amenities. Chen et al. (2015-b) find a non-linear relationship between price and customer satisfaction, due to both the positive effect of quality and the negative effect of the sacrifice needed to purchase the hotel product, while the relationship between price and customer satisfaction can be influenced by the reduction of room occupancy impact. Liu et al. (2014) discover that international hotel chains can set common pricing and rate fence policies for Chinese and Western tourists, as they have similar preferences.

At present, the internet has the potential to influence customer purchase decisions, and with consumer reviews, it has become a new kind of word-of-mouth communication (Sparks and Browning, 2011). Xiang et al. (2015) point out that online reviews on online booking websites are closely linked to customers' hotel experiences and satisfaction, and the content the customers generate on them can be used for understanding their behaviour. They analyse Expedia.com website ratings and content for a specific period of time and find a strong association between consumer experience and satisfaction. In turn, they also notice that the absence of factors like cleanliness and maintenance are a source of dissatisfaction. In an evaluation of consumer ratings and comments on a booking website, Stringam and Gerdes (2010) find that the absence of cleanliness is the most common negative comment, with other negative ratings and comments including the following keywords: 'customer service', 'bathroom' and 'beds'. Meanwhile, 'food and beverages', 'hotel convenience attractions', 'shopping', 'airports', and 'downtown' respond to positive ratings and comments. Sparks and Browning (2011) find that positive reviews and comments have a higher influence on the willingness to book and customer trust in a specific hotel compared to negative ones. Mauri and Minazzi (2013) look at the value and credibility of online comments and find that 75% of respondents check online comments before they book a hotel room. They also detect a positive correlation between the value of the review and a customer's intention to book and their hotel expectations, and that the responses of hotel employees to comments negatively impact customer booking intentions. Noone and McGuire (2013) show that consumer reviews have a major effect on making a hotel purchase, especially the review's valence. The price also has a significant effect on the purchase decision, although negative reviews have a stronger impact than price reductions. Finally, brand name does not have any effect on the purchase decision when different alternatives are considered. Smith (2016) finds a non-linear relationship between a positive or negative variation of the reference price in terms of customer willingness to pay. A price rise has a larger negative effect when compared to the positive effect of a price reduction, and he also finds a limit to price discounts that have no positive effect on sales. Viglia et al. (2016) show that hotels should take care when reducing prices as the reference price perceived by the customer may be affected.

Segmentation by Hotel Categories. Destination heterogeneity makes the agglomeration factor more attractive by reducing consumer search costs (Canina et al.,

2005), and a location close to competitors can assist in the generation of positive externalities in terms of the economic and institutional context (Urtasun and Gutiérrez, 2006). Canina et al. (2005) find that higher levels of differentiation in a competitive cluster have a negative impact on low-cost hotels and a positive impact on luxury and high-priced ones, since their characteristics boost the attractiveness of the area. Urtasun and Gutiérrez (2006) show that the agglomeration in Madrid, with hotels of a similar size and rival service suppliers, leads to more benefits than costs, while an agglomeration of similar-priced hotels gives rise to more costs. Balaguer and Pernías (2013) discover that with the entry of a new competitor in urban hotel contexts, prices will be brought down. When a new competitor in the same category enters the market, the price reduction effect is greater on weekdays and lower at weekends, when there are more leisure travellers. Finally, as the number of competitors rises, it becomes harder to discriminate prices.

Lee and Jang (2011) analyse the airport hotel segment, finding that the hotels are simultaneously affected by their distance to the airport and to the city centre. A hotel's ease-of-access to the airport plays an important role in how it is perceived.

O'Neill and Mattila (2006) find that higher occupancies at lower prices push up hotel profits, as opposed to lower occupancies at higher prices. Hwang and Chang (2003) measure the managerial efficiency of Taiwanese hotels, concluding that resort hotels are better managed than urban ones—mainly due to higher occupancies at weekends—and that hotels serving international guests and international chains are also more efficient.

In terms of market structure, Graf (2011) finds that urban hotels from the more affordable segment can be a potential substitute for high-price hotels when price becomes a decisive factor in tourist consumption decisions. In the event of falling incomes, high-price hotels may fail to gain customers by reducing prices.

1.3. Price Optimization

The optimal pricing determination is a complex process as the hotel has to manage several issues, such as supply availability, customer valuation of the product and expected future demand (Elmaghraby and Keskinocak, 2003).

Initially, an important body of the literature has focused on optimal allocation; in other words, on selling the right amount of inventory at a given price to different segments (Talluri and Van Ryzin, 2005). *Table 1* describes and classifies the most significant literature on optimal allocation.

Table 1. Price Optimization (PO) methods found in literature.

Author	Model scope	Demand model implications				Model/Methodology
		Elasticity of demand	Value/s			
Baker et al. (2002)	Individual Hotel	Not considered			Optimal Allocation	There are different classes willing to pay different rates.
Bitran and Gilbert (1996)						Guests do not check-in at the same time.
Bitran and Mondschein (1995)						Dynamic hotel arrivals.
El Gayar et al. (2011)						Forecasts total demand and booking group segment.
Goldman et al. (2002)						Booking control strategies that allow for the optimization of overlapping stays.
Liu et al. (2002)						Unconstrained demand distributions across the booking horizon.
Desiraju and Shugan (1999)	Individual RM firm					Different market segments that book at different moments across the booking horizon.
Pan (2007)	Aggregate hotel demand					Optimal pricing between the low and high season.
Lee (2011)**	Individual hotel	Airport	-0.043	-0.19	Demand models	Linear demand model.
		Suburban	-0.061	-0.38		
		Urban	-0.078	-0.117		
Canina and Carvell (2005)	Aggregate hotel demand	Total	-0.13			They estimate the number of sold hotel rooms, using room prices, income level and the price of substitute products.
		Upper upscale	-0.15			
		Upscale	-0.11			
		Midprice full service	-			
		Midprice limited service	-0.21			
Damonte et al. (1998)*	Aggregate hotel demand	Economic	-0.31			County level.
		Columbia County	-0.8	-1.8		
Hiemstra and Ismail (1993)	Aggregate hotel demand	Charleston County	-0.1	-0.3		310 hotels divided into high and low-price segments.
		Low-price hotels	-0.35			
Tran (2015)	Aggregate hotel demand	High-price hotels	-0.57			Luxury hotels (Autoregressive Distributed Lag Model).
		Long-run	-0.03			
		Short-run	-0.02			

Chatwin (2000); Feng and Xiao (2000); Gallego and Van Ryzing (1994); Levin et al. (2008)	Individual tourists/RM demand	<i>Theoretical model/simulation</i>		DP model	Poisson process.
Zhao and Zheng (2000)					DP model (Poisson process); Non-homogeneous demand model (numerical example using elasticities: from -1.5 to -3.5)
Aziz et al. (2011)	Hotel	-2	Algorithm to calibrate the elasticity value. The elasticity is constant for the whole hotel.		
Bandinelli (2000)	<i>Theoretical model</i>		Poisson process.		
Bayoumi et al. (2013)	Hotel	-0.4	The demand is estimated using a probit function. The elasticity is constant for the whole period being optimized.		
Guadix et al. (2010)	<i>Theoretical model/simulation</i>		Forecasts the individual and group demands.		
Guo et al. (2013)	<i>Theoretical model/simulation</i>		Develop a theoretical framework to get the optimal number of segment in dynamic models		
Hormby et al. (2010)	Hotel/Group of hotels	Not available	Real-time price elasticity models for different market segments.		
Zhang and Weatherford (2016)	<i>Theoretical model/simulation</i>		Measure the dynamic-pricing deterministic performance when demand/capacity		
Ng (2009)	Service supplier at individual level	<i>Theoretical model/simulation</i>			Advanced and spot demand models for services.
Melis and Piga (2017)	Hotels destinations comparison	<i>Empirical research</i>		DP model	In the online prices of mediterranean resort hotels there is an heterogeneous behaviour in different destinations, higher star rating hotels tend use more DP practices, and the season and booking time also affect the DP practices.
Abrate et al. (2012)					In some European capital cities there are online DP practices. In the leisure segment the price tend to increase along the booking horizon, while the star rating and the availability of rooms use to affect the pricing structure.

Akçay et al. (2010)	Demand for multiple products that use RM	<i>Theoretical model/simulation</i>	MNL consumer choice model	Vertical and horizontal differentiation.	
Arenoe et al. (2015)				Oligopolistic game where the customers choices are taken according to the prices and the importance they give to the hotel attributes.	
Dong et al. (2009)				Dynamic pricing problem under inventory scarcity, together with stock levels and qualities of substitute products.	
Anderson and Chie (2016)				Link the dynamic pricing with the MNL models by considering the choice of hotel attributes.	
Patchon et al. (2007)				Captures corporate clients' choice behaviours under the effect of competition (price elasticity effect on optimal discount).	
Ratliff et al. (2008)				Multiple flights and classes are considered.	
Vinod et al. (2009)				Long-term and short-term pricing (relative fare competitiveness of host carrier, elasticity example: -1.05).	
Sierag et al. (2015)	Individual hotel			Considers hotel cancellations and the overbooking limits, the inclusion of cancellations can increase the revenue by a 20% in the optimal scenario.	
Talluri and Ryzin (2004)	Demand segmentation based on airline fares			MNL model vs. independent demand model: low-price and high-price sensitivity example.	
Zuang et al. (2017)	Individual hotel			Combine capacity control and DP models following a stochastic process under advanced demand information availability, and random customer arrivals and occupation duration.	
Zhang and Weatherford (2016)		Measure the DP stochastic performance when demand/capacity get varied.			
Jacobs et al. (2010)	Demand for airline itinerary/route	Price Balance Statistic: algorithm that optimizes the pricing structure of the different airline segments and the itinerary's scheduled capacity. The elasticities are used as input in the model (example values: -0.5, -1.8, -2.5).			
Suzuki et al. (2001)	Aggregate airline itineraries/routes	Linear regression model	-0.013	Service quality and market share relationship model: comparison of several models.	
		Cobb-Douglas model	-0.495		
		Linearized logit model	-0.638		
		Asymmetric response	- Price - Price		0.385 0.581
Peng et al. (2015)	Aggregate tourism demand	Product	Accommodation	-0.727	Meta-regression international demand model.
Gat (1998)	Urban hotel demand	<i>Theoretical model/simulation</i>		Discrete-choice model and hedonic framework: urban hotels offering different qualities and prices within the same city.	

*Max-min. seasonal elasticity values.

** Max-min. elasticity values of different individual hotels.

Source: Prepared by the author

Cross et al. (2009) and Cross et al. (2011) point out that after the events of 9/11, several stakeholders in the hotel industry realized that product orientation was not enough and they became more consumer-oriented. In hotel management, customer orientation deals with two fundamental factors: pricing and customer value. The thinking behind customer orientation is to set optimal prices and to predict different market segment demands in a dynamic way.

The most widespread model in the literature used to typify customer behaviour is demand function. With this, it is possible to estimate consumer willingness to pay and price elasticity of demand (Shy, 2008). The main demand models used in such literature are (1) linear demand functions (Lee, 2011; Shy, 2008; Suzuki et al., 2001); (2) non-linear demand functions, such as a Cobb-Douglas demand function (Lee, 2011; Shy, 2008; Suzuki et al., 2001), and (3) customer choice demand models, mainly multinomial logit (MNL) (Akçay, et al., 2010; Pachon, 2007; Ratliff, 2008; Talluri and Van Ryzin, 2004). Talluri and Van Ryzin (2005) classify the first two types of models as a deterministic approach—which is suitable when customer sensitivity varies over the booking time—and the third as a stochastic approach which performs better with the random fluctuations of demand and the option of keeping capacity for the future, instead of just selling units. Zhang and Weatherford (2016) in a numerical study compare the performance of DP deterministic and stochastic formulations when demand and capacity proportions vary, and reach similar conclusions. Guizzardi et al. (2017) point out that the hotel room price variation across the booking horizon tends to be non-deterministic. However, in practical terms, as hotels do not usually vary prices so often, the assumption of the stochastic DP trend is not effective. Smith et al. (1992) place demand behaviour in the airline sector as non-linear and stochastic. In turn, Lee (2011) and Lee et al. (2011) point out that demand function estimation is a powerful tool in maximizing revenue as it makes it possible to measure how demand changes under different market conditions and price structures.

When different market segments are taken into consideration, each segment is composed of individuals with homogeneous demand patterns (Ng, 2009). Once the seller is able to differentiate markets, price discrimination can be applied in order to set different prices for each market. In fact, what we see are different interrelated market segments, where a room sold to one type of guest at a specific time cannot be sold in the future due to capacity constraints.

1.3.1. Dynamic Pricing (DP) Models

Optimal DP deals with tourist booking dates, where the customers are willing to pay different amounts of money for the same service as the date of stay approaches, so the problem is to set a pricing policy able to maximize revenue on the date of stay (Bandinelli, 2000). A DP model might be able to maximize revenue by offering a price that reflects current demand and occupancy levels (Ivanov and Zhechev, 2012), so past booking curves and details are useful variables for DP models (El Haddad et al., 2008; Ivanov, 2014). The hotel has to deal with the booking time, demand information and supply availability (Elmaghraby and Keskinocak, 2003). Dynamic models must also reflect different customer behaviours. Each behaviour may undergo different changes

as the date of stay approaches, and customer perceptions and expectations change over time. Talluri and Van Ryzin (2005) highlight some characteristics of the dynamic models: (1) they can be considered as independent-demand processes; (2) they are feasible in competitive markets where the supplier is the price-taker and the customer bases his choice according to his willingness to pay; (3) they seek stability in the relationship between price and demand, and (4) they seek the simplification of optimization pricing procedures. Ng (2009) finds that last-minute demand pays higher prices than advanced demand. Du et al. (2016) show that the change rate of potential demand of individual customers has the power to influence booking time, i.e. when this change rate increases the booking time gets shorter, and the price elasticity of demand affects prices and profits. In practical terms, Abrate et al. (2012) find that the vast majority of hotels in European capital cities use some type of DP. The customer segment, hotel star rating and number of competitors influence pricing policy. Oses et al. (2016) determine that hotels in the Basque Country use DP for the online segment, but these prices are not changed as often. Guizzardi et al. (2017) model the online hotel room price variation along the booking horizon for the business segment in order to predict the best booking strategy. In this way, they find that hotels in business destinations introduce larger discounts along the booking horizon, especially during special events, and secondly, they identify other online price structural determinants such as seasonality, business locations, star rating, hotel facilities and extra services.

Table 1 describes and classifies the most significant literature on DP. For example, taking a product comprising a hotel room booked on certain dates for certain lengths of stay, Lee (2011) makes an in-depth analysis of the hotel PO problem across the booking horizon, subject to the sum of all product demands conditional on the total number of available rooms. Thus, the prices per arrival date and length of stay are dynamically optimized in order to maximize revenue. The model can be easily extended by taking into account different segments, considering different customer types, distribution channels and rate fences. Aziz et al. (2011) develop an integral PO model, where prices are set dynamically. Meanwhile, a simulation is used to estimate arrivals and the different elasticities of demand. This enables an optimal price to be set for each booking time. Bayoumi et al. (2013) develop another integral dynamic model that includes current demand and the price elasticity of demand in a Monte Carlo simulation. The model uses a seasonal reference price which is adjusted using different multipliers: the booking horizon, capacity, length of stay and group size.

1.3.2. Consumer Choice (MNL) Models

Other papers, which mainly focus on the airline sector, describe air traffic as a whole, where each route can be operated by different carriers with different flight schedules. Air traffic is segmented into different classes, and although price changes will directly influence one class, this accounts for just part of the sum of all the segments or classes (Jacobs et al., 2010; Pachon et al., 2007; Ratliff, 2008; Vinod et al., 2009). Thus, each segment has its own elasticity, meaning that a price change to a specific segment will have a direct effect on the demand in that segment, but the variation in the demand will affect the total traffic to a lesser extent. Consequently, in the optimization process, the remaining segments will be allocated a different amount of available seats, a

phenomenon known as cross-price elasticity effects (Jacobs et al., 2010). Therefore, customer choice models consider the interdependence of different segments, can represent the heterogeneity of preferences of these segments, and they are also able to model uncertainty and a large range of customer behaviours, even when they are unpredictable (Talluri and Van Ryzin, 2015).

MNL models are quite popular in a random utility framework; their objective is to maximize the random utilities of each alternative (Anderson and Xie, 2016). They are used to capture customer choice probabilities and measure their utility based on the use of historical data (Akçay, et al., 2010; Pachon, 2007; Ratliff, 2008; Talluri and Van Ryzin, 2004; Zuang et al., 2017). MNL models consider that individual demands are affected by different known attributes and so their effects influence consumer choices. *Table 1* describes and classifies the most significant literature on customer choice models.

1.3.3. Price Elasticity of Demand

When the empirical evidence and available literature on elasticity strategies and applications were examined, we find that Roberts (2003) indicates that by measuring the price elasticity of demand, prices can be optimized at different points in time. The suggested solution is to estimate a market demand value for each customer segment. Desiraju and Shugan (1999) finds that a pricing strategy in the service sector is more profitable when dealing with different markets purchasing the service at different times. Perakis and Sood (2004) observe that prices are higher during periods with lower price sensitivities, and lower when there is a bigger available inventory for the whole horizon. Du et al. (2016) find that the elasticity price of demand influences room prices and hotel profit. Rondan-Cataluña and Rosa-Diaz (2014) use value for money and pricing for segmenting hotel customers, price-elastic and price-inelastic segments. They show that the price of a night in a room and the hotel's additional expenses are not suitable for segmenting both groups. On the one hand, the elastic segment considers hotels prices reasonable, has a positive perception of the price-quality relationship and has a good perception of the hotel's value; consequently, they are willing to pay an additional 6%. On the other hand, the inelastic segment exhibits lower levels of price perception, value for money, and the price-quality relationship, so they are not willing to pay more for the product, although their level of loyalty is higher.

Using an algorithm to optimize the pricing structure of different airline segments and the scheduled capacity of the origin-destination pair, Jacobs et al. (2010) point out that elasticity values are often difficult to measure. They consider that the best models for estimating the elasticity of demand are MNL models. Likewise, using a consumer choice model, Vinod et al. (2009) point out that in the optimization process, the most difficult task is to calibrate price elasticities due to the heterogeneity of available flight data, i.e. itinerary, timing, carrier, market share, fare information, etc. *Table 1* summarizes the different hotel demand models and elasticity measures found in the relevant literature.

In this same context, several authors (Cross et al., 2009, Canina and Carvell, 2005 and, Enz et al., 2009) point out that most of the demand models cited in the literature on the subject estimate market price elasticities instead of property-level demands. Meanwhile, Graf (2011) indicates that this literature mainly focuses on absolute demand, without taking into consideration how demand moves from one segment to another. In this respect, Canina and Carvell (2005) highlight the fact that the level of sensitivity to economic factors is lower in the case of property-level demand. In order to estimate the number of rooms sold across different urban hotel market segments, they use room prices, income levels and the prices of substitute products. In fact, economic and mid-price hotels display higher elasticity values. Lee (2011) evaluates different linear demand models across airport, suburban, and urban hotels, with the following explanatory variables: price, days between the booking and arrival date, length of stay and the day of arrival within the week. In general terms, she finds that the demand is highly inelastic and that the same type of individual hotel in similar locations displays similar demand patterns. Aziz et al. (2011) use a probit function to estimate demand, finding that hotel demand is highly elastic and constant for the whole period that is being optimized. Bayoumi et al. (2013) develop an algorithm in order to calibrate the elasticity value from a hotel's historical data, finding that demand is inelastic and constant for the whole hotel.

1.3.4. Competitive Demand Effects

Increasing competition in the tourism sector is forcing companies to reconsider their pricing and sales strategies (Akçay et al., 2010). The typical case study in the literature is the emergence of low-cost airlines after deregulation of the airline industry, which completely transformed the sector (Pachon et al., 2007). The hotel industry is usually defined as a highly competitive market (Hung et al., 2010; Kim et al., 2004; Lee, 2011). The lack of differentiation in the hotel market places pricing as the unique purchase driver in the consumer process, and the remaining factors are replaced solely by the price variable (Viglia et al., 2016).

At this point, it is necessary to define who the hotel's competitors are. Strglobal.com, a hotel data benchmarking company, defines the hotel competitive set as a group of hotels that compete for business and which are selected by the managers to measure hotel performance. Stuart-Hill (2013) proposes the following factors for the hotel competitive set selection: (1) market segmentation and understanding customer business mix; (2) the number of competitors; (3) location; (4) reference price ranges of the different segments of customers; (5) online ratings and comments as a source of information, and (6) the assessment of competitive strengths.

Moving to the main results found in the literature, Vinod et al. (2009) emphasize that setting prices above those of the competition can give a company an undesirable image, while prices below those of the competition may result in lost profit margins, price wars and a negative brand image. In turn, Jacobs et al. (2010) point out that a lack of capacity in a market can lead to the potential entry of competitors as prices rise. Pachon et al. (2007) indicate that market share models must capture the price elasticity of demand, as well as service substitutability levels, since in a competitive

market, low substitutability indicates inelastic demand while high substitutability is a sign of elastic demand. Abrate and Viglia (2016) find that a rise in the number of local competitors has a negative impact on prices in the urban hotel segment. Likewise, Balaguer and Pernías (2013) determine that the entry of a new competitor in Madrid reduces prices by 0.8-1.9%. Kim et al. (2004) indicate that a competitive approach based on competitor prices may not be optimal. However, they find that optimal prices are determined by the competition and by a hotel's position in relation to its competitors. Through a higher level of differentiation, hotels can set higher prices, with reputation and brand image being two factors that affect differentiation. Lee (2016) finds that competitors setting discounts increases the possibility of a price reduction and that small hotels seem to be less affected by competitors' prices. Revenue managers have to check the prices of competitors and nearby hotels before taking a pricing decision, and where competitors have equal or lower prices, they should consider a price cut. Hotel price discounts can also be a way to stand out from competitors. Enz et al. (2009) point out the importance of competitor price variations on pricing decisions, although sometimes a drop in prices is not compatible with maintaining high quality levels. They analyse competitors' pricing behaviours in local markets, as the products compete directly with their closest competitors, although consumers might be tempted to move to another market in the event of a big variation in price. In their findings, they outline the effects on hotel occupancy and average prices due to the influence of direct competitors. They conclude that a methodology is needed to measure own and cross-price elasticity values across different market segments and locations using hotel data. Viglia et al. (2016) estimate varying consumer fairness perceptions depending on hotel strategies. They find that customers lower their reference price when competing hotels adjust their prices at the same time; the leader-follower strategy presents a higher reference price and the independent pricing strategy presents the highest one. Chung (2000), meanwhile, claims that demand segments are partly determined by the category of hotel, i.e. luxury accommodation does not compete with low-price hotels, although competition among different hotel categories is not totally inexistent, especially in the case of similar or equivalent products. Similarly, Becerra et al. (2013) outlines how vertical differentiation (hotel star rating level) better resists competitive price pressures compared to horizontal differentiation (belonging to a hotel chain). The higher vertical differentiation allows the hotel to set larger levels of prices, reducing discounted rates and combatting increased competition. Lee (2015) finds high price competition among Texas hotels at the local level but hotel quality differentiation diminishes the difference between competitive price effects. In addition, when other hotel variables are considered at the same time, their proximity to attractions is found to have a positive impact on prices, while hotel size or city centre location, congestion or noise have a negative effect. In the Houston hotel market, Kim et al. (2016) identify a city centre location as the only variable affecting hotel location, having a positive impact on hotel performance, while noise and congestion have a negative impact. In terms of seasonality, they find that hotels have a decreasing performance throughout the year. Silva (2015) analyses hotel chain establishments competing in several markets in terms of lower price competition due to multimarket contact (contact among firms in more geographical markets does not intensify competition between them) and differentiation effects. Larger levels of multimarket contact allow higher prices (lower competitiveness) where hotels

competing in the same market do not use a branding strategy. The introduction of hotel differentiation in multimarket contact results in lower levels of competitiveness for three-star hotels, while higher multimarket contact in one/two-star and differentiated service hotels leads to lower prices. Graf (2011) evaluates substitutability in urban hotel segments and the results support the theory that changes in personal income have a segment substitution effect, but changes in absolute demand for each segment may also affect market share. The results also show that for low-scale accommodation consumers do not move to higher-priced hotels, whereas demand for upscale accommodation can be attracted to lower-priced hotels where there are bigger price differences between the different segments; consequently, low-scale accommodation competes for customers in more price ranges than upscale hotels.

In empirical analyses, Lee (2011) and Lee et al. (2011) stress the differences in competitiveness between the airline and hotel sectors. Seasonal pricing differences and different price evolutions across the booking horizon by the two sectors are explained by: (1) different capacity constraints, (2) greater differentiation, and (3) the fact that hotels have a greater ability to differentiate the customer experience through amenities and quality of service. Lee (2011) points out that RM strategies should take into account factors like prices or the competition in circumstances in which there is remaining high-price capacity or low-occupancy forecasts. In turn, where only inventory scarcity is considered, traditional airline RM combined with responses to own and competitor prices is a good strategy. Abrate and Viglia (2016) emphasize the effect of free cancellation rate fences across booking horizon prices on competitive industry environments. DP is less effective with free cancellation policies, something not usually found in the airline or railway industry, and it may neutralize some commonly used RM tools.

Other sectors in direct competition with hotels are the hostel sector or shared economy, i.e., online rental accommodation such as Airbnb. On the one hand, in a hedonic pricing study applied to the hostel sector, De Oliveira Santos (2016) finds that the most important attributes to positively affect hostel prices are cleanliness, location and facilities. On the other hand, in the shared economy sector, Wang and Nicolau (2017) highlight the effect on rental prices of the host profile, which behaves like a quality measure that is able to replace the hotel star rating, in addition to the accommodation's attributes, rental rules, reviews, location, amenities and services. Similarly, in a shared economy study, Abrate and Viglia (2017) point out the importance of the host and product reputational factors in the revenue optimization procedure, which are used to reduce transaction risk and uncertainty.

1.4. Discussion and Conclusions

The purpose of this article was to describe and classify the main revenue management and price optimization techniques found in the hotel sector. The task was quite challenging as we had to relate the empirical evidence and literature available to the main factors associated with hotel RM, i.e. different types of market segmentation

Table 2. RM techniques: Customer segmentation and Price optimization.

Topic		Topic Description		Main References		
Customer segmentation	Internal segmentation	Booking dates		<i>Abrate et al. (2012); Aziz et al. (2011); Bandinelli (2000); Lee (2011); Lee et al. (2011); Lee (2016)</i>		
		Rate fences	Rules used to segment demand and justify differential pricing	Customer self-segmentation	<i>Coenders et al. (2003); Ivanov and Zhechev (2012); Lee (2011); Narangajavana et al. (2014); Ng (2009); Wu et al. (2012); Yimaz et al. (2016)</i>	
				Barriers customer has to meet		
		Tourist types		Differential pricing according to the customers valuation of the hotel product, i.e. leisure vs. business segments	<i>Abrate et al. (2012); Dolnicar (2002); Gallego and Van Ryzin (1994); Guadix et al. (2010); Ivanov (2014); Lee (2011); Maier and Johanson (2013); Yavas and Babakus (2005)</i>	
	Seasonality		Demand variability caused by natural or institutional factors	<i>Coenders et al. (2003); Collins and Parsa (2006); Gallego and Van Ryzin (1994); Juaneda et al. (2011); Lee (2011); Lee et al. (2011); Pan (2007)</i>		
	External segmentation	Reservation systems	Traditional intermediaries	Their roles are: representation, design and promotion of tourism packages, and advertising and promotion.	<i>Aguiló et al. (2001); Aguiló et al. (2003); Bastakis et al. (2004); Chen et al. (2015-a); Kim et al. (2009); Huang et al. (2010)</i>	
			Internet	It has replaced traditional intermediaries, making prices more transparent and the market more competitive.	<i>Abrate et al. (2012); Demirciftci et al. (2010); Du et al. (2016); Guo et al. (2013); Guo et al. (2014); Ivanov and Piddubna (2016); Kim et al. (2009); Ling et al. (2014); Varini et al. (2003)</i>	
		Hotel differentiation	Hedonic pricing		Hotel attributes and characteristics valuation. Allows customer segmentation but does not consider consumers' willingness to pay.	<i>Abrate et al. (2011); Abrate and Viglia (2016); Aguiló et al. (2001); Aguiló et al. (2003); Balaguer and Pernías (2013); Coenders et al. (2003); Corgel et al. (2015); De la Peña et al. (2016); Espinet et al. (2003); Ivanov and Piddubna (2016); Juaneda et al. (2011); Latinopoulos (2018); Lee and Jang (2011); Monty and Skidmore (2003); Papatheodorou (2002); Soler and Gémár (2016); Thrane (2005); Thrane (2007); Tochaiwat and Likitanupak (2017); White and Milligan (2002); Yang et al. (2016)</i>
			Consumer hotel valuation	Customer assessment.	Hotel attributes/services	<i>Chen et al. (2015-b); Danziger et al. (2006); Dolnicar (2002); Heo and Hyun (2015); Huang (2015); Kang et al. (2004); Liu et al. (2014); Shieh et al. (2014); Tsaor and Tzeng (1996)</i>
					Online ratings/comments and pricing	<i>Mauri and Minazzi (2013); Noone and McGuire (2013); Smith (2016); Sparks and Browning (2011); Stringam and Gerdes (2010); Viglia et al. (2016); Xiang et al. (2015)</i>
Segmentation by hotel categories			Hotel location, agglomeration and type (or hotel differentiation) factors have implications for hotel categories.		<i>Balaguer and Pernías (2013); Canina et al. (2005); Graf (2011); Hwang and Chang (2003); Lee and Jang (2011); O'Neill and Mattila (2006); Urtasun and Gutiérrez (2006)</i>	

Price optimization	Dynamic pricing models	They maximize the hotel revenue by offering prices that reflects current demand and occupancy levels. They identify different customer/segment behaviours.	<i>Abrate et al. (2011); Aziz et al. (2013); Bandinelli (2000); Bayoumi et al. (2013); Chatwin (2000); Feng and Xiao (2000); Gallego and Van Ryzing (1994); Guadix et al. (2010); Guizzard et al. (2017); Guo et al. (2013); Hormby et al. (2010); Levin et al. (2008); Melis and Piga (2017); Ng (2009); Talluri and Van Ryzin (2005); Zhang and Weatherford (2016); Zhao and Zheng (2000)</i>
	Consumer choice models	Consider the interdependence of different segments, MNL model.	<i>Akçay et al. (2010); Anderson and Chie (2016); Arenoe et al. (2015); Dong et al. (2009); Jacobs et al. (2010); Patchon et al. (2007); Ratliff et al. (2008); Sierag et al. (2015); Suzuki et al. (2001); Talluri and Ryzin (2004); Vinod et al. (2009); Zhang and Weatherford (2016)</i>
	Price elasticity of demand	Price elasticity of demand estimation, i.e. demand function estimation is used to segment demand, as well as to charge the correct price to every segment.	<i>Canina and Carvell (2005); Damonte et al. (1998); Hiemstra and Ismail (1993); Lee (2011); Tran (2015)</i>
	Competitive demand effects	The hotel industry is usually defined as a highly competitive market, but the specific sector's differentiation possibilities influence its final effect.	<i>Abrate and Viglia (2016); Balaguer and Pernías (2013); Becerra et al. (2013); Chung (2000); Enz et al. (2009); Graf (2011); Lee (2011); Kim et al. (2014); Kim et al. (2016); Lee et al. (2011); Lee (2015); Lee (2016); Silva (2015); Viglia et al. (2016)</i>

Source: Prepared by the author.

caused by different pricing, together with PO processes and the main variables that affect them, such as the price elasticity of demand and competition. *Table 2* sets out all this information as analysed in the article.

The value of this paper resides in the fact that it is a global study aimed at synthesizing and classifying all hotel RM techniques with implications on pricing and customer segmentation. It also identifies the main trends that offer an insight into the current situation, as well as pinpointing future fields of research.

With the development of ICT in the hotel sector, aggregate pricing studies have been able to move towards research at an individual hotel level (Anderson and Xie, 2010), since large amounts of data and their real-time availability have made it possible to focus on single hotels and pricing issues. In parallel, new technologies and market developments have contributed to the transformation of pricing processes from inventory controls to a customer-oriented approach, allowing hotels to improve their response to changes in demand while also ensuring more accurate customer segmentation. Mattila and Gao (2016) point out that future ICT development will contribute to making prices more transparent and improve consumer price perception, with consumers being able to pay through mobile devices, and make them less sensitive to price. They indicate the emergence of new segments and the need to educate them about the use of DP practices; from this perspective the loyalty is a segment that is seeing increased importance in the hotel sector and requires special focus, as well as being sensitive to DP practices. DP practices will also vary across different cultures and the urban nature of the markets.

Knowledge of demand and its reaction to price variations are therefore key factors to take into account in any optimization model with maximum revenue expectations. However, the competitor pricing effect on demand is different in the hotel sector to the airline sector due to their specific characteristics. Although the hotel sector is considered to be highly competitive, the potential for differentiation and individual specific hotel policies reduce the typical pressure of competitive environments; subsequently, current research should focus in-depth on the role of competitor pricing in the optimization process, particularly at individual hotel level.

The pricing threshold time effect on hotel performance is another factor that revenue managers should consider in the decision-making process. As Kim et al. (2016) indicate, active RM has positive short-run results in the hotel market in exchange for poorer performance in the long-run. Therefore, RM pricing decisions can have several extents within the threshold time and all of these need to be considered for immediate and long-term hotel revenue maximization.

As we have seen, it is a relatively new field of research. The literature review shows that most studies have been conducted over the past 25 years. This is an emerging field of study, with increasing numbers of researchers focusing on it. Consequently, further empirical work is needed to improve our understanding of customer behaviour so as to ensure more accurate segmentation and help develop more holistic PO methods at hotel level, thus helping to boost hotel revenues (Hornby et al., 2010).

1.5. Bibliography

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Chapter 2. Online Hotel Demand Model and Own-Price Elasticities: An Empirical Application to two Resort Hotels in a Mature Destination

Abstract

Pricing is a basic strategic tool in hotel revenue management. This study proposes a particular demand function model for resort hotels for measuring their own-price elasticities, along with the different seasonal demands, and across the booking horizons. The model is applied to the online transient demand for two hotels in Majorca –a well-known, mature mass tourism destination– in order to estimate and compare different elasticities, which could be used by revenue management departments to correctly manage prices in the short-run and establish optimum pricing strategies (over the medium- and long-run). The results show that the two hotels display completely different own-price elasticities during high season, while during low season, demand is quite inelastic at both hotels; secondly, common price variations among seasons or hotels may sometimes be an erroneous pricing strategy, such as the common early booking strategy. The model is easily adaptable to different hotels.

Keywords

Own-price elasticity, Pricing, Revenue management, Hotel demand, Booking time

2.1 Introduction

Several factors determine hotel price variability, the most important ones in the resort tourism sector are: (1) seasonality (Aguiló et al., 2001; Coenders et al., 2003; Narangajavana et. al., 2014), where the price of a room booked in peak season is expected to be much higher than in low season; (2) the booking date (Padhi and Aggarwal, 2011; Schütze, 2008; Schwartz, 2008), since the price of a room booked six months in advance cannot be the same as that of a room booked on the start date of a stay, and the same applies to rooms booked three months in advance during either the low or high season (Noone and Mattila, 2009); and (3) the type of reservation, since the same hotel may have different kinds of rooms and/or services or different reservation conditions (Coenders et al., 2003; Ivanov and Zhechev, 2012; Padhi and Aggarwal, 2011; Narangajavana et. al., 2014; Von Martens and Hilbert, 2009).

Certain characteristics of the hotel sector, such as perishability, capacity limitations, or seasonality, make occupancy and demand management key factors in determining revenue. Revenue management (RM) deals precisely with this issue, since it can be defined as the application of an information system and pricing in order to ensure the right capacity at the right time in the right place so as to maximize revenue (Legohérel et al., 2013; Ivanov and Zhechev, 2012), meanwhile revenue managers only have past demand and price information at their disposal (Padhi and Aggarwal, 2011). However, short term revenue maximization, due to the hotel capacity limitations –as the number of hotel rooms cannot be changed–, is only determined by demand management

(Coenders et al., 2003). Thus, the RM applicability depends on three factors (Legohérel et al., 2013; Ivanov and Zhechev, 2012; Vives et al., 2018a): (1) the possibility of advance bookings; (2) the ability to manage price variations across the booking horizon; and (3) the possibility of segmenting demand into homogeneous groups according to price sensitivities.

Pricing is the basic strategic tool in hotel RM (Cheng et al., 2011). Through price variations, a revenue manager can adjust demand at times when available occupancy differs from the occupancy that might maximize revenue (Vives et al., 2018a). Thus, it is essential to estimate the different demand curves in order to set prices that will optimize revenue for the different seasons and across the booking horizon.

Plenty of articles can be found that attempt to establish the best pricing strategy in RM contexts, related particularly to the airline and hotel sectors. One basic pricing tool is price discrimination (Ivanov and Zhechev, 2012), where a hotel will vary prices according to the type of guest as opposed to the type of room or the cost of the service, mainly based on the different price sensitivities of each market segment; dynamic models are one example of price discrimination across the booking horizon (Aziz et al., 2011; Bayoumi et al., 2013; Chatwin 2000; Feng and Xiao, 2000; Gallego and van Ryzin, 1994). Another popular tool is a price optimization consumer choice model, which measures individual demands and their relationships in order to ascertain market responses to price variations (Patchon et al., 2007; Ratliff et al., 2008; Suzuki et al., 2001; Talluri and van Ryzin, 2004; Vinod et al., 2009). However, the easiest and most direct way of measuring market reactions to price variations is to estimate own-price elasticities of demand, through a demand function. Shy (2008) highlights that the demand function is the best way for representing the demand behavior, because it allows representing the demand level as a function of prices and other variables, and at the same time it is an essential condition in the election of the best strategy that allows revenue maximization. Lee (2011) points out that the demand function is easily estimable and provides measures of statistical validity that allow stating its performance. Additionally, she highlights that the demand functions can be easily reproduced for hotels that share similar characteristics as they exhibit similar driver variables, while the fact of missing some of these variable could significantly bias the estimations. Thus, with the demand functions the price elasticity of demand is obtained, a key measure for studying and comparing the application of pricing policies and the financial performance of different hotels or segments. The elasticity measures the quantity demand changes to small price variations, so the fact of estimating different elasticities allows the costumers segmentation (Shy, 2008). For instance, the elasticities enable the demand segmentation across the booking horizon, as well as to set the optimal prices that allow reaching the maximum revenue at the date of stay (Desiraju and Shugan, 1999). Therefore, price elasticity of demand is a key measure that has a direct and short-term effect on bookings and revenue, while it represents a homogeneous measure that allows the comparison of the demand behavior across different times and hotels. However, although the literature on models analyzing changes in demand and its sensitivity is widely extended, in most of cases the variables from these models were not converted into elasticity figures. Some studies point out that the elasticity is something difficult to measure (Vinod et al., 2009; Jacobs et al.,

2010), and the majority of the demand models available in the literature estimate general market price elasticities (Cross et al., 2009; Canina and Carvell, 2005).

A critical step for the RM department, in its bid to maximize revenue, is to estimate demand response to price variations, particularly in the case of the resort hotel sector, which is increasingly impacted by the emerging online transient segment. It is essential to identify different price sensitivities throughout different seasonal demands and across booking horizons in order to set the right price at the right time, especially at the property level when the objective is to maximize revenues with the traditional RM tools. Consequently, this paper attempts to fill a current gap in the literature by presenting a specific demand model for resort hotels aimed at measuring own-price elasticity values throughout different seasonal transient demands and across booking horizons. The model simplicity makes it easily adaptable to different hotel typologies and also allows the aggregation of data in order to estimate joint demand functions of several hotels within the same or similar destinations, due partially to the transformation, simplification, and harmonization process presented for the hotel data variables (these variables are detailed in sections 3 and 4). The availability of own-price elasticity values will enable analysis and comparison across the different booking times, seasonal demands and among different hotels, in such a way as to allow the possibility of supporting or rejecting affirmations such as: hotel resort demand during peak season is inelastic while low season demand is elastic, or early bookings are more elastic when compared to bookings made close to the holiday date. Furthermore, we design a demand model specifically focused on measuring the seasonal and booking time effects, and price variation effects of the online transient demand segment of resort hotels; and additionally, we present an empirical application to test the model applicability, using data of two resort hotels in Majorca, where we estimate and compare seasonal elasticities. We have found no evidence in literature on the resort hotel sector of studies that provide such a broad analysis of the estimation and comparison of elasticities at the hotel level.

Data from two four-star hotels in Majorca belonging to the same multinational hotel chain was used for testing the demand model empirical application.¹

The structure of this paper is organized as follows. Section 2 presents a literature review focused on pricing and elasticity within the framework of RM. Section 3 describes the methodology, where the demand function model is presented. Section 4 describes the data from the two resort hotels used in the study. Section 5 outlines and discusses the results with regard to own-price elasticities and, finally, in section 6, we discuss the implications of the results in terms of pricing and RM strategies.

2.2 Literature Review

2.2.1. External hotel price variation

¹ Thanks to a collaboration agreement with the multinational chain, the firm provided raw data on online transient bookings and prices.

Prices are a strategic factor for the tourism sector, especially when the product sold is perishable, with capacity limitations, large fluctuations and heterogeneous demand (Ivanov and Zhechev, 2012; Narangajavana et al., 2014; Von Martens and Hilbert, 2009). In an empirical study from a demand perspective, Varini et al. (2002) found that the price factor is considered the most important attribute for hotel guests. However, from the hoteliers' standpoint several factors influence prices, for example, the hedonic pricing method tries to capture hotel price heterogeneity among different hotel establishments (Vives et al., 2018a).² Regarding the hedonic pricing methodology, the hotel star category is the most common attribute influencing the price level mentioned in the resort hotel sector literature (Abrate and Viglia, 2016; Aguiló et al., 2001; Aguiló et al., 2003; Balaguer and Pernías, 2013; Coenders et al., 2003; Juaneda et al., 2011; Vives et al., 2018a). A second popular factor mentioned in the literature is hotel location, or distance to the beach or city centre (Aguiló et al., 2003; Balaguer and Pernías, 2013; Coenders et al., 2003; Espinet et al., 2003; Juaneda et al., 2011; Thrane, 2007; White and Mulligan, 2002). Finally, other attributes are present in the literature such as board type (Aguiló et al., 2001; Aguiló et al., 2003; Juaneda et al., 2011; White and Mulligan, 2002), hotel and room characteristics (Abrate and Viglia, 2016; Aguiló et al., 2003; Coenders et al., 2003; Thrane, 2007; White and Mulligan, 2002), and hotel surroundings such as temperature, or economic features of the region (Balaguer and Pernías, 2013; White and Mulligan, 2002).

2.2.2. Internal hotel price variation

At the hotel level one of the main sources of price variation is seasonality; it usually comes from natural –associated with temperature, weather, and climate– or institutional factors –associated with school holidays, religious festivals or other special events– (Lim and Chan, 2009; Vives et al., 2018a). This phenomenon can lead to high fluctuations in demand (i.e. between low and peak seasons) and customers may encounter different prices for the same product (Narangajavana et al., 2014). In this vein, Coenders et al. (2003) analyzed resort hotel prices and found that peak season prices can double or more than double prices in low season. Varying prices can help to strategically shift purchases from periods with high demand to periods with low demand (Chávez and Ruiz, 2005). Juaneda et al. (2011) find that not only do low season prices double during the peak season in Mediterranean resort hotels, but also that this phenomenon is more important in the Balearic Islands compared with other Mediterranean destinations. Their results also show slight seasonal differences among different accommodation establishments, hotels vs. apartments.

The RM literature also deals with other types of resort hotel price variation. From an RM perspective an unoccupied room represents a loss of revenue and so hotels can increase bookings by differentiating prices, offering rooms at discount rates in order to attract price-sensitive customers. Hotels face a trade-off between selling a high number of rooms at a discount rate versus selling fewer rooms at a higher price

² The hedonic pricing method does not enable consumer's willingness to pay to be identified (Aguiló et al., 2001). The responsibility for solving this pricing aspect is RM, which also deals with other problems such as product perishability and capacity limitations.

(Ropero, 2011). The fact of selling the same product at different rates is known as customer segmentation (Ivanov and Zhechev, 2012). In RM, heterogeneous demand and its fluctuations lead to customer segmentation, depending on sensitivity levels to price variations and interrelations among each of these segments. Another common form of customer segmentation in RM is by booking date (Schütze, 2008; Vives et al., 2018a). However, other types of segmentation may be possible, depending on the type of product and customer expectations. Thus, pricing and appropriate forms of customer segmentation can help to push up revenue (Bandinelli, 2000).

2.2.3. Demand behaviour and dynamic pricing formulation

At the short run the hotel industry aims to achieve the right number of guests at the right price, dependent on hotels' limited capacity, as a means of maximizing income (Steed and Gu, 2005).

Specifically, the demand models used in RM are able to quantify the number of sales when price changes and to consider different demand behaviours. The main demand models used in relevant hotel literature are (Vives et al., 2018): (1) linear demand functions (Lee, 2011; Shy, 2008; Suzuki et al., 2001); (2) non-linear demand functions, such as the Cobb-Douglas function (Lee, 2011; Shy, 2008; Suzuki et al., 2001); and (3) customer choice demand models, such as a logit model (Suzuki et al., 2001; Talluri and van Ryzin 2004) or multinomial logit (MNL) (Anderson and Xie, 2016; Akçay et al., 2010; Pachon, 2007; Ratliff, 2008; Talluri and van Ryzin, 2004).

The way of considering the different demand behaviours in these models is through the market segmentation, where each segment comprises individuals with homogeneous demand patterns (Ng, 2009). Once the seller is able to differentiate markets, price discrimination can be applied in order to set different prices for each market (Vives et al., 2018a), since each segment may display different elasticity values.

The interrelation of different hotel market segments forces to consider the different demand behaviours and how they can affect each other; for example, a room sold to one type of guest at a specific time cannot be sold in the future due to capacity constraints. In that sense, when considering the demand modelling together with the demand segmentation, Talluri and van Ryzin (2005), Vives et al. (2018), and Zhang and Weatherford (2016) identify deterministic and stochastic optimal models that present the following characteristics in the revenue maximization process (Table 1).

Table 1 – Characteristics of deterministic and stochastic approaches in optimal pricing models

Approach	Models	Demand	Suitability
Deterministic	Linear and non-linear demand functions	Perfectly predictable, sets the price elasticity of demand	Perform better when the sensitivity of customer varies along the booking time
Stochastic	Customer choice demand models	Stochastic demand, the product is booked before its consumption, it is never perfectly predictable. Sets elasticities and cross-price elasticities	Perform better with the random fluctuations of demand and the possibility of keeping capacity for the future

Source: Own elaboration.

In this context, deterministic dynamic pricing models are a popular tool that can be used to optimize demand through prices that seek to maximize hotel revenue (Aziz et al., 2011; Bayoumi et al., 2013; Lee, 2011), taking into account a hotel's capacity

constraints (Narangajavana et al., 2014). A hotel using dynamic pricing might be able to maximize its revenue by offering a price that reflects the current demand and occupancy levels (Vives et al., 2018a). Therefore, the price it charges will vary according to the demand and occupancy levels (Ivanov and Zhechev, 2012).

Meanwhile, the stochastic dynamic pricing models have mainly been used in the airline sector. Normally, these models are used to describe air traffic as a whole, where different companies can operate each route and set different flight schedules. In that sense, the air traffic is segmented into different categories, and although price changes will directly influence one category, this just represents part of the sum of all the segments or categories (Jacobs et al., 2010; Pachon et al., 2007; Ratliff et al., 2008; Vinod et al., 2009; Vives et al., 2018a). Therefore, each of these segments have their own elasticities, meaning that a price change to a specific segment will have a direct effect on this segment, but the demand variation will also affect the rest of segments, a phenomenon known as cross-price elasticity effects (Jacobs et al., 2010).

In terms of Internet dynamic pricing practices, Abrate et al. (2012) find that the dynamic pricing have presence in the majority of hotels located in the main European capital cities. Oses et al. (2016) obtain a similar result in hotels located in the Basque Country, but these prices do not change regularly. Guizzardi et al. (2017) detect that hotels located in business destination set larger discounts across the booking horizon to the business segment, particularly at special events.

2.2.4. Price elasticity of demand

Once we have described the main models used in the hotel RM literature, the next step is the analysis of the empirical evidence and available literature on elasticity strategies and their applications. In that sense Roberts (2003) points out that measuring the price elasticity of demand allows for price optimization across time and hence revenue maximization. He argues that it is possible to measure how many people pay a certain price, but not how many people are willing to pay it. Thus, the solution he suggests for revenue maximization is to estimate a market demand, for measuring the price elasticity of demand, and he proposes to estimate the price elasticity for each customer segment. Desiraju and Shugan (1999) find that a pricing strategy in the service sector is more profitable when dealing with different markets arriving to purchase the service at different times, although each segment must display different price elasticities. Perakis and Sood (2004) explore the multi-period pricing problem of perishable products in a competitive market. They observe that the price is higher in periods with lower price sensitivities, and that a lower price is set when the available inventory for the whole horizon is greater. Based on the assumption often considered in the RM hotel sector, according to which “customers who book later are willing to pay higher rates”, in an empirical analysis, Lee et al. (2011) prove that rates, particularly rates for the retail segment, do not increase as the day of arrival approaches. This result is different to the one found in the airline sector; where for example, the leisure segment usually books earlier compared with the business segment, and the first segment is defined as the most sensitive, therefore, the typical price path is one where price increases along the booking horizon (Narangajavana et.

al., 2014; Talluri and van Ryzin, 2005). Lee et al. (2011) find three possible explanations for this: (1) different capacity constraints; (2) greater differentiation; and (3) a greater ability to differentiate customer experiences through amenities and service quality.

Jacobs et al. (2010) use an algorithm to optimize RM factors as the pricing structure of the different airline segments and the origin and destination pair scheduled capacity – the elasticities of demand are used in the model as an input– and indicate that elasticity values are often difficult to measure. For these authors the best models for estimating the demand elasticity are the MNL models. Likewise, Vinod et al. (2009) use a consumer choice model and show that in the optimization process it is very difficult to calibrate price elasticities, due to the heterogeneity of data available among flights, i.e. itinerary, timing, carrier, market share, fares information, etc.

There are several studies that estimate different demand models and display elasticity values related to the hotel sector (e.g. Damonte et al., 1998; Hiemstra and Ismail, 1993; Tran, 2015). Tran (2015) develop a demand model for luxury hotel rooms in the US, where factors such as the income level of the origin country of the tourists, the average daily rate of a room at a certain date, and the exchange rate are considered. He finds different types of reactions when facing hotel price and income variations depending on the nationality of the tourist, and in general the demand is highly price-inelastic. Hiemstra and Ismail (1993) find that the hotel demand is largely inelastic and it is more inelastic for the low-price lodging segment compared with the high-price segment. Damonte et al. (1998) compare the aggregate lodging demand from two adjacent different counties located in South Carolina and detect high statistical differences between the seasonal elasticities for the two counties. Rondan-Cataluña and Rosa-Diaz (2014) segment the hotel customers in two: an elastic demand segment and inelastic demand segment according to their price perception. The inelastic segment is not willing to pay more for the hotel product, while the elastic segment is willing to pay an additional 6%.

In practical studies of the application of RM using a database of private companies, Hormby et al. (2010) develop an optimal pricing model for helping Marriot International sales managers, it uses price-elasticities for each market segment in order to set the optimal prices, and also use inventory controls. The customer segmentation comes from the hypothesis that their sensitivity varies according to the booking date, group size, and season. Cross et al. (2009) point out that IHG (Intercontinental Hotels Group) estimated price elasticity values for specific brands in specific regions, and now they are able to simulate multiple demand contexts that allow the revenue maximization at the hotel level.

Precisely, Cross et al. (2009), Canina and Carvell (2005), and Enz et al. (2009) and Vives et al. (2018a) observe that most of the demand models available in the literature estimate market price elasticities instead of hotel level demands. Graf (2011) indicates that the literature mainly focuses on absolute demand and it is not considering how demand moves from one segment to another. In that sense, Canina and Carvell (2005) point out that the level of sensitivity to economic factors is lower for property-level demand. They use the room prices, the income level, and the rate of substitute

products in order to estimate the number of rooms sold across different urban hotel market segments. Their results show that the higher elasticity values are found in the economic and mid-price limited service hotel markets. Lee (2011) analyses and compares different linear demand models across different hotels types –airport, suburban, and urban– and different U.S. locations where the hotel demand is explained by the following variables: price, days between the booking date and arrival date, length of stay, and day of the week of arrival. Her results show that the demand is really inelastic and the same type of individual hotels in similar locations show similar demand patterns.

Table 2- Elasticity values for hotel demand in the literature.

Article	Demand Scope	Demand type	Elasticity values	
			Max.	Min.
Rosselló et al. (2005)	Aggregate demand	German tourists	-0.84	
		UK tourists	-0.98	
		France tourists	-4.18	
		Netherlands tourists	-0.51	
Aziz et al. (2011)	Individual hotel demand	Hotel	-2	
Bayoumi et al. (2013)	Individual hotel demand	Hotel	-0.4	
		Total	-0.13	
		Upper Upscale	-0.15	
		Upscale	-0.11	
Canina and Carvell (2005)	Individual hotel demand	Midprice Full-Service	-	
		Midprice Limited Service	-0.21	
		Economy	-0.31	
Damonte et al. (1998)	Aggregate demand	Columbia County	-0.8	-1.8
		Charleston County	-0.1	-0.3
Hiemstra and Ismail (1993)	Aggregate demand	Low-price hotels	-0.35	
		High-price hotels	-0.57	
Hormby et al. (2010)	Individual hotel demand		Not available	
Lee (2011)	Individual hotel demand	Airport	-0.043	-0.19
		Suburban	-0.061	-0.38
		Urban	-0.078	-0.117
Tran (2015)	Aggregate demand	Long-run	-0.03	
		Short-run	-0.02	

* Max-Min. seasonal elasticity values.

** Max-Min. elasticity values from different individual hotels.

Source: Own elaboration.

Table 2 gathers the hotel elasticity values estimated in the literature. In general terms the elasticities estimated are very static and the demand is usually inelastic, only Damonte et al. (1998) show seasonal differences in elasticity values. Furthermore, this literature does not exhibit different elasticity values across the booking horizon, something we try to do in this paper.

Finally, the development of Information and Communication Technologies has had an enormous impact on pricing strategies in the hotel sector (Vives et al., 2018a). Through online reservation systems, customers search for better deals and try to find better

strategies to get better rates and increase total utility. In fact, Schwartz (2008) points out that price-sensitive customers make internet reservations in order to protect themselves from future price fluctuations. The internet helps to reduce the information gap between hoteliers and consumers, and, as Ropero (2011) indicates, customers try to get a better deal through internet searches and by booking at the right time. Online transient demand has become an increasing demand segment in the hotel sector and, hence, tourism firms are devoting a lot of resources and efforts to this segment. Consequently, from the supply point of view, internet represents a new market segment where rates have to be optimized in order to maximize revenues. Internet also represents an opportunity to analyze real-time data that may allow for better price and cost adjustments, while contributing to hotel differentiation (Ropero, 2011).

2.2.5 Concluding remarks

Various strategies can be used to identify and estimate different hotel demand behaviours. As mentioned in the literature review section, the most widespread models that enable demand behaviour to be taken into account are the dynamic models. However, the literature focuses on analyzing changes in demand and sensitivities, but these are rarely converted into elasticity figures that allow their comparison along different seasons and booking times, as well as among different hotels. Furthermore, in dynamic models, the demand curve only represents one step towards revenue maximization, since the objective is to set prices that maximize revenue, taking into consideration the hotel's limited capacity.

Nevertheless, the main concept that can be taken into consideration with dynamic models is that demand shifts across the booking horizon. In practical terms, when it comes to the daily performance in the number of hotel bookings, there can be many days during the earliest stage of the booking horizon where no room is sold for a specific date of stay. Meanwhile, there will be certain points across the booking horizon, usually during the periods closest to the date of stay, when several rooms are sold. Likewise, at any point in the horizon, there may be days when several reservations are made, alternated with other days with no or very few bookings. Thus, in order to harmonize and take into account all these possible erratic daily variations, the proposed solution is to work with average daily reservations (demand intensity is used by Chatwin, 2000 and Feng and Gallego, 1996).

Price is another essential factor in a demand function. When a reservation is made, the customer pays a price that, among other things, depends on the seasonal price, booking time, number of guests, board, type of room and payment method. Additionally, in the short-term, the RM department varies prices in order to alter demand and obtain higher revenue from the hotel's limited capacity. Therefore, in tactical terms, only those short-run price variations and early booking offers allow for revenue maximization across the booking horizon. Hence, these price variations can respond to the following factors: a change in demand behaviour or capacity limitations.

The purpose then of relating demand response to price variations, i.e. demand intensity during the period of time where prices remain unaltered, is: (1) short-run

tactical optimization of RM; and (2) data simplification and harmonization (less erraticism), without this representing a significant loss of information –this is the assumption where due to historical data availability and revenue manager experience, the reaction to any demand oscillation with a price variation response is immediate.

In short, estimating the demand function is the easiest direct way of assessing the demand behaviour, through own-price elasticity figures. Thus, the strategy followed in the paper is to define different demand functions for homogeneous stay periods (under the assumption that the closer the date of stay, the more similar a demand pattern is) and booking periods, allowing for time differences within these periods, in order to capture the temporal and price effects on reservations (demand intensity). Therefore, the estimated own-price elasticity values are going to be directly comparable among these different seasons and booking times, and hotels, and will allow understanding the hotel differential pricing. The different elasticity values will be useful for analyzing demand behaviour, setting the best pricing policy at each time (short-run), and identifying the most elastic-inelastic periods in order to set the best pricing policy in the medium-term.

2.3 Methodology

In the theoretical model, the hotel demand function is defined as follows:

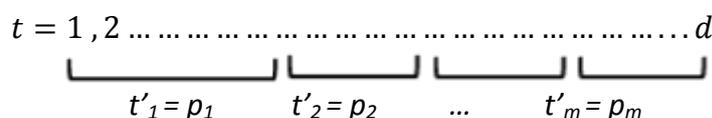
$$Q_t^d = f(P_t^d, R_t^d)$$

Where Q represents the daily room reservations made for a specific date of stay in the booking horizon t ($t=1,2, \dots, d$ where d is a specific date of stay); P is the price set for the hotel on the booking date and R is the gap between the booking date and date of stay d –where the booking time period is a continuous interval (Chatwin,2000).

As the demand for date of stay d might be very similar to the demand for $d+1, d+2, d+3\dots$, all these demands can be grouped together in a homogeneous group, a , as Shy (2008) groups together homogenous periods of time in the same function.

$$\sum_{a=d,d+1,d+2,\dots,d+A} Q_t^a = f(P_t^a, R_t^a)$$

The next step is to transform the daily room reservations (Q) into the average daily room reservations (q) (i.e., we will obtain the demand intensity similarly to Chatwin, 2000 and Feng and Gallego, 1996) for the period of time across the booking horizon where P remains constant, i.e. the period of time where the RM department does not shift the price, either by short-term price variations or early booking offers:



Hence, the average daily room reservation can be defined as:

$$q_{t'}^a = f(P_{t'}^a; r_{t'}^a; s_{t'}^a)$$

Where r is the average R during the period of time that P remains constant; and s are the number of days that P remains constant.

The different demand functions are estimated every time the demand structure changes due to seasonal (Shy, 2008) and booking period effects (Ng, 2009). Specifically, the demand model specification is a log-linear functional form, as the log-linear form is quite extended in the literature given its coefficient can be easily interpreted, where a 1% price variation is associated with a $\beta \times 1\%$ variation in the daily room reservations, i.e. the price elasticity of demand (Canina and Carvell, 2005; Coenders et al., 2003; Shy, 2008; Thrane, 2007; Tran, 2015).

$$\ln q_{t'}^a = \alpha_0 + \text{dummies} + \beta_p \cdot \ln P_{t'}^a + \beta_r \cdot \ln r_{t'}^a + \beta_s \cdot \ln s_{t'}^a$$

where the dummies are included as in Tran (2015) and the dummies considered specifically in our model are the following:

$$\text{Dummies}_{y,d,b} = \sum_{y=1,2,\dots,Y} \beta_y D_y + \sum_{d=1,2,\dots,D} \beta_d D_d + \sum_{b=1,2,\dots,B} \beta_b D_b$$

Where:

y : 2013, 2014, and 2015, represents the year/season factor.

D_y : is the dummy variable *Year/Season*, which takes the value 1 when the observation belongs to a specific season and 0 otherwise.

d : mm-dd, mm-dd+1, mm-dd+2,..., mm-dd+A, represents the date of stay factor.

D_d : is the dummy variable *Date of stay*, which takes the value 1 when the observation belongs to a specific date of stay and 0 otherwise (Lee, 2011). The *Date of stay* variable is grouped in 20-25 days periods during the time the hotel remains open.

b : mm, mm+1,...,mm+n, represents the booking period factor, it is usually grouped by month or half a month, depending on the moment along the booking horizon—normally the dates closer to the date of stay require more observations due to the booking activity.

D_p : is the dummy variable *Booking period*, which takes the value 1 when the observation belongs to a specific reservation period and 0 otherwise. This group of dummies divide the booking horizon into discrete intervals (Lee, 2011; Perakis and Sood, 2004).

2.4 Data

The empirical demand model is tested through an application to two 4-star hotels located in Majorca belonging to a multinational hotel chain from one of the top four in the Balearic Islands. Majorca is a well-known mature mass tourism Mediterranean destination mainly specializing in resort tourism (Aguiló et al., 2001, 2003). The importance of the island's tourism industry cannot be denied, as many of Europe and Spain's leading multinational hotel companies have their headquarters on the island and, in 2016, Majorca supplied more than 292,000 beds and welcomed almost 11 million tourists, almost one third came during the summer months (from June to September), with almost 70% of tourists choosing to stay at a hotel or similar (CAIB, 2017). The hotel sector generated in 2016 more than 45 million overnight hotel stays, generating a total expenditure of 11.6 billion euros (IBESTAT, 2018). Regarding the hotel chain, it owns fifteen 4- or 5-star hotels on the island and operates over 100 hotels in 16 countries worldwide (Iberostar, 2016a), most located next to a beach (97% of them are resort hotels). Its hotel and resort division has an international workforce of over 23,000 people and the company reported a turnover of 1.107 billion euro in 2013 (Iberostar, 2016b).

The two hotels are located in different tourist areas of the Majorcan coastline. The first hotel has 619 rooms (*Hotel 1*) and the second has 360 rooms (*Hotel 2*). The study focuses on transient online reservations from 2013 to 2015, accounting for a 32% of the total reservations in the *hotel 1* and a 35% in the *hotel 2* (data from 2016), while the rest are sold through tour operators (TO) channels. Nevertheless, during the last three years both hotels have significantly increased their online transient demand, which demonstrates the importance and emergence of the online segment for resort hotels. Focusing to the seasonal prices, during the peak season online prices are a 115-120% higher than low season prices, and between a 35 and 41% of the yearly reservations take place.

With regard to tourism profile, both hotels present the following features:

- In *hotel 1* slightly more than 30% of demand comes from German tourists and 20% from Spanish tourists; while in *hotel 2* almost 40% of demand comes from German tourists and 12% from Spanish tourists. In both hotels, 17-18% of demand comes from British tourists.
- Two-thirds of tourists going to *hotel 1* are families and the rest are couples, while the percentage of couples in *hotel 2* is 10% higher.
- 90% of reservations in terms of board type are all inclusive for *hotel 1*, while for *hotel 2* only 50% are all inclusive.
- On average, *hotel 2* has the longest stay reservations, 8 days vs. 7.5 days.
- 33% of reservations in *hotel 1* take place over the last 30 days before the date of stay, and just 26% of them take place during that period in *hotel 2*.

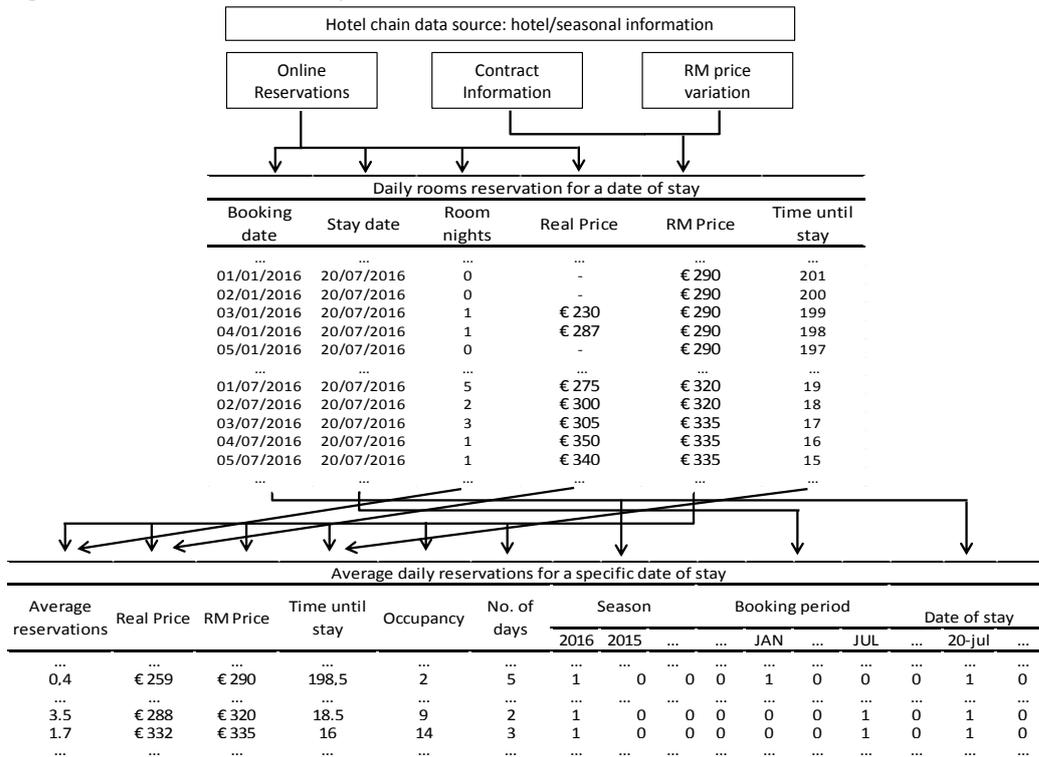
Three sources of information provided by the hotel chain were used:

1. *Contract information*: This refers to seasonal prices. The prices are structured as per Baur et al. (2013), and they can vary depending on the stay period, type of room, type of board, guest type, booking date, length of stay and payment method. According to the demand pattern of tourism in Majorca, the lowest prices coincide with the opening and closure of the hotel while the highest

prices are charged during the summer months of July and August (CAIB, 2017).³ As for the booking dates, each *contract* sets two or three discounts in order to boost demand during the earliest booking period.

2. *Online reservations*: This refers to online reservation data. All reservations contain the same information: the arrival date, booking date, cancellation date, room nights, number of guests, type of room, total price etc. The information is displayed in a similar format to that described by Bordea et al. (2009).
3. *RM price variation*: The revenue manager can change the price of one or more days' stay depending on the booking date, sales rate and occupancy level.

Figure 1- Data transformation process



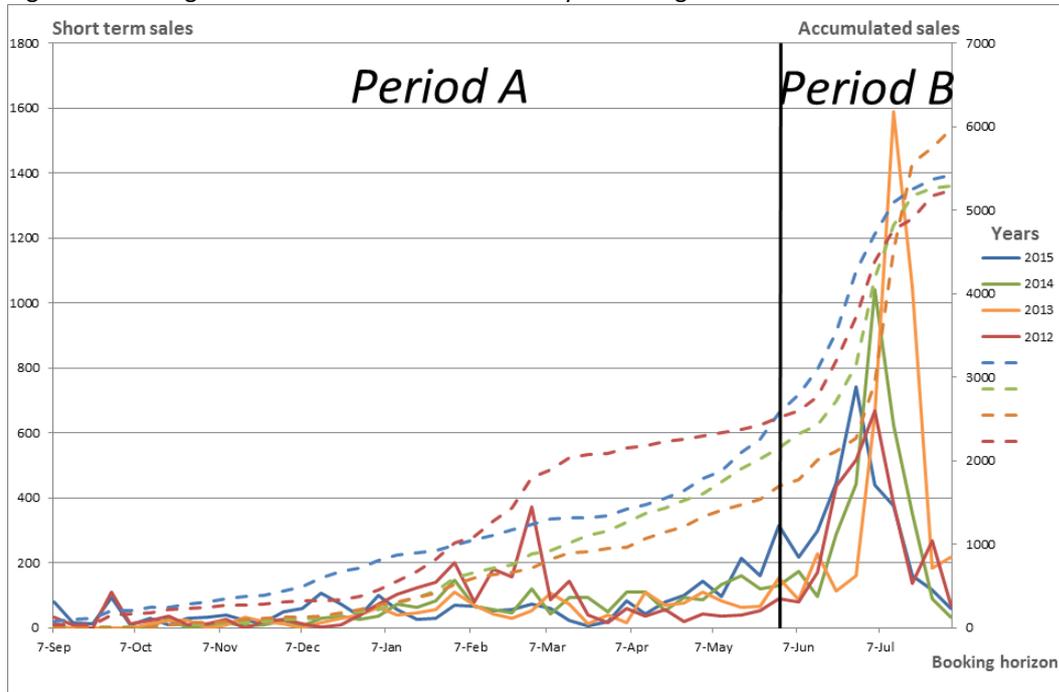
Source: Own elaboration.

We present an empirical application of the methodological model, using the online transient reservation data for the two aforementioned Majorcan hotels. The online transient segment has been chosen as it is an emerging and dynamic new segment in the resort hotel sector, where RM departments are focusing most of their efforts. The objective is to analyze the different demand functions of the two hotels during homogeneous stay periods as the booking date draws closer to the arrival date. In other words, the aim is to analyze how own-price elasticities of demand affect hotel sales. The three available sources of information have to be transformed to meet our

³ In that specific case, the Majorcan resort tourism seasonal price variation depends on the specific date of stay, as the prices increase from low season (March-April) to peak season (July-August) and go down again (September-October). Therefore, the weekday and weekend effects are not reflected on prices due to the island's resort tourism characteristics and the fact that the average length of stay is one week.

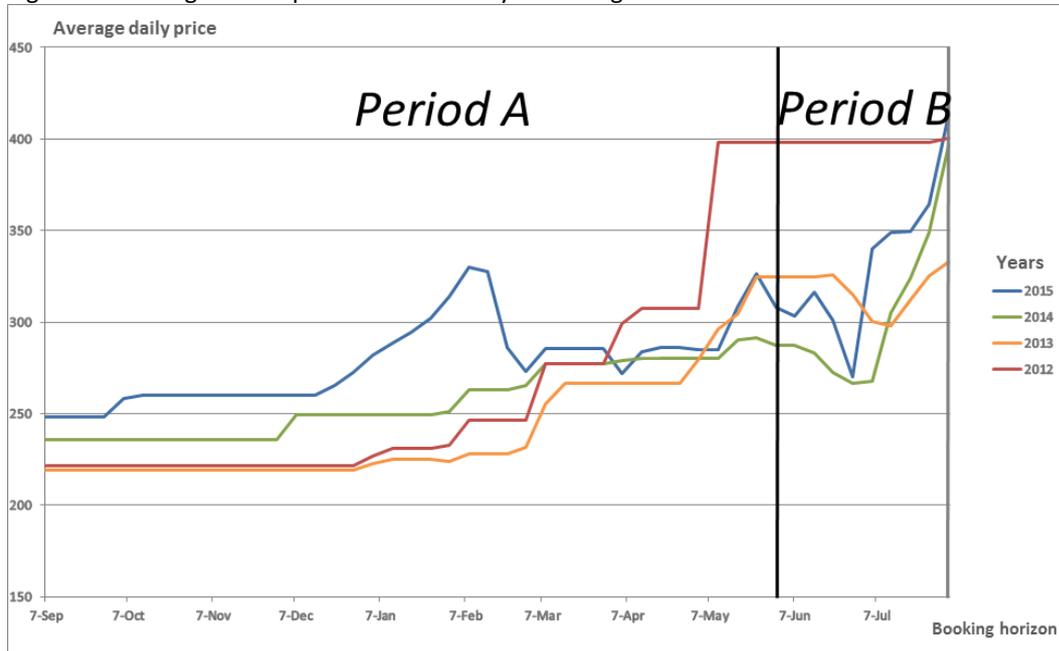
methodological requirements. This data transformation process is described in Figure 1.

Figure 2- Booking horizon reservations from 18th July to 5th August at *Hotel 1*



Source: Own elaboration.

Figure 3- Booking horizon prices from 18th July to 5th August at *Hotel 1*



Source: Own elaboration.

The supplied *online reservations* data is transformed into room reservations for each booking date and date of stay. The dates of stay are grouped into homogeneous periods, usually the stay periods where prices remain unchanged in the *contract information*. There are two available reservation prices: (1) the *Real Price*, which is the price paid by the customer when the reservation is made, dependent on the seasonal

price, booking time, number of guests, type of board, type of room, payment method, etc., as reflected in the *Contract information*; while (2) the *RM Price* is the average room rate defined by the RM department.⁴ The *RM Price* only reflects seasonal price variability (i.e. price fluctuations due to the date of stay and booking time) and this theoretical daily price can be calculated from the *contract information* and *RM price variation* data. Hung et al. (2010) define the *RM Price* as a proxy for the *Real Price*. Thus, both prices can be used. However, the *Real Price* is only observed when a reservation is made, while daily information for the *RM Price* can be found even if there is no reservation.

The second step is to transform the *daily room reservations* for a specific date of stay in the booking horizon into the *average daily room reservations* (demand intensity) for homogeneous periods. The starting point for this is the *RM Price* variability, which only fluctuates across the booking horizon due to temporal factors. Thus, each homogeneous period (observation) is the period where the *RM Price* remains unaltered. During this time, there will be an absolute number of reservations and these are transformed into the *average daily room reservations*. The same transformation is carried out for the rest of the variables: *Real Price* (average), *Time until stay*, and *Days*.

Looking at the data for *Hotel 1*, a comparison of the sales evolution of rooms for the period from July 18th to August 5th (an example of the peak season) and reservations across the booking horizon from 2012 to 2015 (*Figure 2*) we can identify two well-differentiated periods: (1) from the earliest booking period to June 1st, where the booking pace is very low (*Period A*), while (2) during the last 7-10 weeks, the pace increases substantially and half the total room night reservations are made (*Period B*). *Figure 3* shows the evolution of prices for *Hotel 1*. *Period A* displays the lowest prices (early booking offers) with rates that rise quite slowly, while prices undergo huge variations during *Period B*, reaching a maximum at the end of the booking horizon. If the information from both graphs is combined, we can identify a structural change in the booking pace and prices and hence we can conclude that: (1) *Period A* accounts for the lowest levels of reservations and lowest prices; (2) prices are on average 20-25% higher during *Period B* and this period accounts for half the total reserved room nights; and (3) bookings reach a peak when price discounts are given during the second period. These results might indicate that the second demand period is more elastic. Therefore, the booking horizon can be divided into two homogeneous demand periods (*Period A* and *Period B*).

In short, when the periods of stay with the lowest and highest demands are compared, prices for the online transient segment can be seen to increase exponentially, sometimes even tripling. The most extended segmentation strategy followed by the hotel chain's RM department is based on price variations according to the date of stay and booking date.

⁴ Revenue managers work with theoretical prices (*RM Price*) – that is, with average reservation prices obtained from historical reservation data (Bayoumi et al., 2013) - and they only reflect seasonal price variability.

2.5 Results and Discussion

Taking as an example the information from the data section for *Hotel 1* - stays from July 18th to August 5th -, *Table 3* shows the values of the coefficients of the estimated variables in the three demand functions –depending on the different booking horizon considered. The Dy_y –year/season dummy variables are seen to have a negative coefficient during reservation *period A* –meaning that sales were higher in previous years, as compared with the reference year (2015)– and a positive coefficient in *Period B*, except for the previous year (2014). The results indicate that the Dd_d – *Date of stay* dummy variables are normally not significant and so the stay period considered is relatively homogeneous. The Db_b – *Booking period* dummy variables have a coefficient with different values depending on the function definition and booking period.

Table 3- Examples of demand function regressions (*Hotel 1* – period of stay from July 18th to August 5th)

		Period A:		Period B:		Total Period:	
		Reservation Periods					
		9-1-2014-1 to 6-3-2015		6-4-2015 to 8-5-2015		9-1-2014-1 to 8-5-2015	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
<i>Constant</i>		11.76***	6.85	10.48***	9.23	7.01***	12.52
$Dyear_y$	2014	-0.16***	5.34	-0.12**	-8.64	-0.13***	-3.93
	2013	-0.25***	-7.64	0.11**	-1.97	-0.11***	-3.32
	2012	-0.06**	-2.23	0.92***	6.34	0.06	1.45
$Ddays_d$	20-Jul 21-Jul	0.005	2.53	0.017	0.18	0.027	0.59
	22-Jul 23-Jul	-0.019	-0.53	0.121	1.29	0.048	1.04
	24-Jul 25-Jul	-0.046	-1.28	0.100	1.04	0.031	0.68
	26-Jul 27-Jul	-0.069*	-1.95	0.165	1.62	0.032	0.70
	28-Jul 29-Jul	-0.091**	-2.50	0.052	0.52	0.019	0.41
	30-Jul 31-Jul	-0.104***	-2.88	-0.135	-1.39	-0.052	-1.15
	1-Aug 2-Aug	-0.052	-1.45	-0.209**	-2.10	-0.049	-1.07
	3-Aug 5-Aug	0.030	-1.56	-0.066	-0.62	0.047	1.10
	$DBooPer_{dp}$	1-Jan 31-Jan	0.21***	7.20	-	-	0.06
1-Feb 28-Feb		0.20***	6.21	-	-	0.01	0.19
1-Mar 15-Mar		0.16***	3.79	-	-	-0.08	-1.48
16-Mar 31-Mar		-0.29***	-5.00	-	-	-0.20***	-2.57
1-Apr 15-Apr		0.34***	4.69	-	-	0.05	0.48
16-Apr 30-Apr		-0.08	-1.23	-	-	0.03	0.32
1-May 15-May		-0.003	-0.09	-	-	-0.10**	-,01
15-May 30-May		0.07	1.18	-	-	0.18***	3.41
1-Jun 15-Jun		-	-	-0.79***	-7.88	-0.32***	-5.91
16-Jun 30-Jun	-	-	-0.10	-1.60	0.17***	4.35	
1-Jul 15-Jul	-	-	0.20***	0.43	0.35***	7.97	
$\ln p^A_{t'}$		-0.83***	-9.83	-1.65***	-8.64	-1.11***	-12.07
$\ln res^A_{t'}$		-2.24***	-3.19	0.15	0.98	0.66***	9.40
$(\ln res^A_{t'})^2$		0.18**	2.53	0.01	0.43	-0.13***	-12.51
$\ln days^A_{t'}$		-0.03	-1.56	-0.06	-1.50	-0.07***	-4.15
R^2		0.54		0.61		0.75	
Adjusted R^2		0.52		0.59		0.74	
(P-value)		0.00		0.00		0.00	

* Significant at the 90% significance level.

** Significant at the 95% significance level.

*** Significant at the 99% significance level.

Source: Own elaboration.

For example, in the first two weeks of June, sales drop, whereas in the first two weeks of July, they rise (*Period B* and *Total Period*). When focusing on prices ($\ln p^a_{it}$), results show that these are inelastic during *Period A*, very elastic during *Period B*, and slightly elastic when both periods are jointly considered, in contrast to most of the elasticities displayed in the literature. The global effect of r –the difference between the date of stay and the booking date variables ($\ln r^a_{it}$ and $(\ln r^a_{it})^2$)– is negative during the earliest reservations but positive as the date of stay approaches, the *days* variable ($\ln s^a_{it}$) is only significant when both periods are jointly considered (*Total Period*). In the case of this last variable, as this variable increases the larger the negative effect on sales. This means that on the earliest booking dates, the price remains constant for longer periods and this has a negative effect on reservations.

Table 4. Comparison of Seasonal/year elasticities from both Hotels 2015 and 2012-2015, and RM Price and Real Price (Absolute values).

HOTEL 1										
Stay date		Booking period			2015	2014	2012-2015	2015	2014	2012-2015
12-May	3-Jun	Per A	1-Sep	26-Mar	0.02	(+)0.47***	0.14	0.7***	0.54***	0.74***
		Per B	8-Mar	3-Jun	0.71***	1.05***	0.73***			
4-Jun	25-Jun	Per A	1-Sep	25-Apr	0.64***	0.28***	0.85***	0.86***	0.79***	1.03***
		Per B	27-Mar	25-Jun	0.7***	1.1***	0.99***			
26-Jun	17-Jul	Per A	1-Sep	7-May	1.11***	0.51***	1.14***	1.38***	1.28***	1.52***
		Per B	3-May	17-Jul	1.71***	1.68***	2.16***			
18-Jul	5-Aug	Per A	1-Sep	3-Jun	0.83***	0.58***	1.2***	1.11***	0.93***	2.12***
		Per B	29-May	5-Aug	1.65***	1.11***	2.77***			
6-Aug	24-Aug	Per A	1-Sep	2-Jun	0.39***	0.12**	0.56***	0.35***	0.31***	1.27***
		Per B	17-Jun	24-Aug	0.9***	0.75***	1.78***			
25-Aug	13-Sep	Per A	1-Sep	6-Jul	0.78***	0.51***	0.95***	0.96***	0.9***	1.06***
		Per B	3-Jun	13-Sep	1.13***	0.92***	1.47***			
14-Sep	7-Oct	Per A	1-Sep	5-Aug	0.44***	0.44***	0.19***	0.61***	0.69***	0.73***
		Per B	17-Jul	7-Oct	0.95***	1.02***	1.43***			
HOTEL 2										
Stay date		Booking period			2015	2014	2012-2015	2015	2014	2012-2015
27-Mar	21-Apr	Per A	1-Sep	31-Jan	0.29**	(+)0.30	0.14	0.56***	(+)0.07	0.27***
		Per B	1-Feb	21-Apr	0.65***	(+)0.10	0.33**			
22-Apr	15-May	Per A	1-Sep	26-Feb	0.45***	0.36***	0.39***	0.55***	0.34***	0.48***
		Per B	27-Feb	15-May	0.41***	0.38***	0.22***			
16-May	3-Jun	Per A	1-Sep	7-Mar	0.73***	0.72***	0.69***	0.76***	0.74***	0.81***
		Per B	8-Mar	3-Jun	0.83***	0.88***	0.79***			
4-Jun	25-Jun	Per A	1-Sep	26-Mar	0.33***	0.46***	0.46***	0.49***	0.54***	0.67***
		Per B	27-Mar	25-Jun	0.59***	0.54***	0.66***			
26-Jun	17-Jul	Per A	1-Sep	2-May	1.56***	1.61***	1.58***	1.18***	1.17***	1.16***
		Per B	3-May	17-Jul	0.4**	1.2***	0.48***			
18-Jul	5-Aug	Per A	1-Sep	28-May	1.91***	1.45***	1.58***	1.16***	1.13***	1.15***
		Per B	29-May	5-Aug	1.05***	1.13***	0.92***			
6-Aug	24-Aug	Per A	1-Sep	16-Jun	0.65***	0.72***	0.8***	0.44***	0.47***	0.62***
		Per B	17-Jun	24-Aug	0.28***	0.3***	0.68***			
25-Aug	13-Sep	Per A	1-Sep	2-Jun	0.47***	0.54***	0.56***	0.55***	0.53***	0.67***
		Per B	3-Jun	13-Sep	0.45***	0.34**	0.66***			
14-Sep	7-Oct	Per A	1-Sep	16-Jul	0.63***	0.42***	0.59***	0.66***	0.56***	0.74***
		Per B	17-Jul	7-Oct	0.47***	0.48***	0.63***			

Source: Own elaboration.

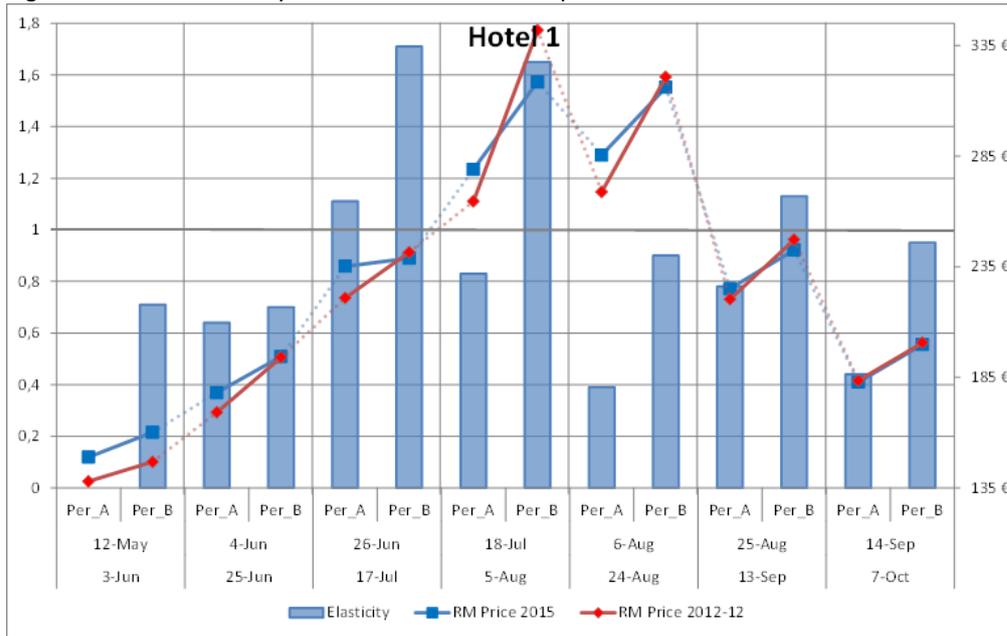
Table 4 shows a comparison of Hotel 1's seasonal elasticities obtained from the different demand functions. The highest elasticities appear during *Period B*, the period closest to the stay date. This might seem surprising, as literature on RM usually regards the earliest booking periods as being the most elastic, which could explain the early booking discounts applied by the company, from the 28% discount for 2012 to the 15% discount for 2015. However, two additional factors should be considered: (1) prices

during *Period A* are 20-25% lower than those of *Period B*, i.e. the price of reference is different for the two periods. Thus there is a bigger response by demand to price discounts in late reservations; and (2) as Lee et al. (2011) point out, the assumption that customers who book later are willing to pay higher rates does not always hold true, due to the greater differentiation and higher ability to differentiate customer experience in the hotel industry when compared to the airline sector. In this instance, a similar outcome was observed with the elasticities obtained for the different the seasonal periods of stay, i.e. the most elastic demand coincides with the peak in high season, and the prices are two or even three times higher than those in low season. Regarding the *Real Price* elasticity values are more inelastic but equivalent to the *RM Price* elasticity values.

Table 4 also shows information on own-price elasticity values obtained by estimating the different demand functions for *Hotel 2*. Overall, *Hotel 2* seems to have a much more inelastic demand than *Hotel 1*. Even so, both hotels have identical early booking strategies. The most elastic demand, in the case of *Hotel 2*, corresponds to reservations made during *Period A* of the high season, while this is precisely when *Hotel 1* has the lowest elasticities. Hence, the opposite elasticity values at the two hotels indicates that the same pricing strategy cannot be applied to both hotels, it could represent a badly formulated pricing strategy, particularly in the case of idle capacities on a stay date. Furthermore, the *Real Price* elasticity values for *Hotel 2* are closer to the *RM Price* (i.e. the individual price of a specific date of stay). The main differences between the two hotels that could help to explain these elasticity differences are: (1) *Hotel 2* is located in a very well-known area of Majorca, with about 240% more beds than the area where *Hotel 1* stands (CAIB, 2017). According to Aguiló et al. (2003), a hotel's location is an important source of price variation, and their findings indicate also opposite elasticity values depending on tourist nationalities. Consequently, factors such as the popularity and proximity of particular areas may determine the possibility of product differentiation, with direct effects on price and elasticity. (2) *Hotel 1* has a 60% additional room capacity, as well as online reservations, than *Hotel 2*, while *Hotel 2* sells rooms with an average price 14% higher than *Hotel 1*. Indeed, Pan (2007) points out that a hotel's room capacity negatively affects optimal room rates. (3) The consumer profile is different in the two hotels, *Hotel 1* is more specialized in the national segment, families, all-inclusive board and late bookings compared to the *Hotel 2*. Therefore, according to Lee et al. (2011) it could involve different consumer willingness-to-pay.

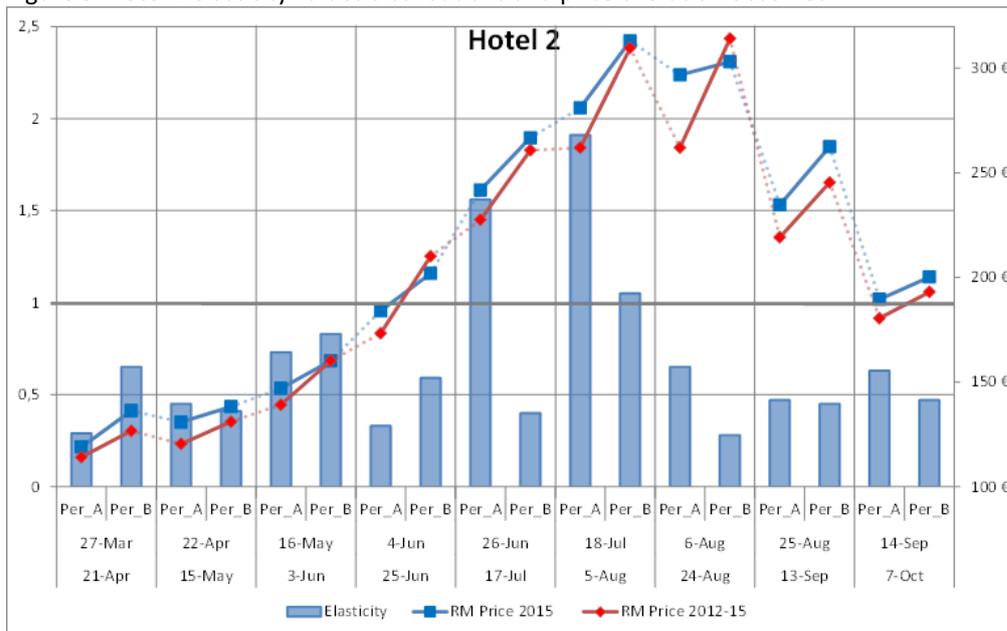
Finally, *Table 4* also proves the stability of all the elasticity measures for both hotels along the different seasons/years. We present the average elasticities for all the seasons considered in the demand functions (2012-2015) and we compare those with the actual values for year 2015. Results indicate that the differences of the elasticities between the season 2015 and the average values from all the seasons only present small differences. In general, the last season (2015) presents a slightly more elastic demand, especially in the case of *Hotel 1*. Therefore, the differences of the elasticity values are due to the differences across the booking time demand behaviour, *Periods A* and *B*, and between the characteristics of demand from the two hotels.

Figure 4. Hotel 1 elasticity values distributions and price evolution observed



Source: Own elaboration.

Figure 5. Hotel 2 elasticity values distributions and price evolution observed



Source: Own elaboration.

Figures 4-5 compare the two hotels seasonal and booking time (period A-B) elasticities with observed RM Prices –the prices set for the revenue managers in 2015 and the average prices between 2012-15. We can see that although the price distribution is quite similar, the hotels’ elasticities take significantly different values. For instance, in high season *Hotel 1* and *Hotel 2* tend to increase prices during period A and to maintain or reduce prices in period B, while the *Hotel 1* usually has the most elastic demand in period B and *Hotel 2* during the period A, so it could indicate that an erroneous pricing strategy in *Hotel 2* is being used, particularly when we see that both hotels set the same early booking discounts (period A). It can be explained by the fact that in hotel

chains the same revenue manager administers several hotels, usually located in the same destination, and tends to use similar price strategies.

In summary, the demand model designed in the present article detects significant different demand behaviours along the different seasons and booking times, and between the two Majorcan hotels.

2.6 Conclusions

Estimating a demand curve is a basic step in a pricing optimization process. When a pricing strategy is defined in order to maximize revenue, it is essential to measure the response of the demand to price variations. In fact, knowledge of demand response to price variations is a key tool in hotel sector pricing management. This is especially true in the emerging segments for resort hotels the online transient demand, particularly in the case of mature destinations needing to diversify in today's current competitive scenario.

More specifically, this empirical study presents a particular demand model to measure the seasonal and booking time variation of different own-price elasticities of demand at hotel level. Furthermore, we present an empirical application to try to understand the different pricing strategies for online transient demand for two resort hotels in Majorca, where elasticity estimations allow comparison of own-price elasticity values across the different stay dates and booking times for the same hotel, as well as between the two hotels. The simplicity of the current model makes it easily adaptable and applicable to other hotel typology and it also allows the aggregation of the hotels' data in order to estimate joint demand functions and the estimations will still be comparable among them. Another contribution of the present paper is the transformation, simplification, and harmonization process of the hotel data variables used by the RM department, which enables the application of this particular demand model to other hotels and makes their results' comparison possible.

By measuring different price sensitivities, not only can this help the RM departments to set the best price at each point in the booking horizon (short-term), thus maximizing revenue (Roberts, 2003), but it can also help to define the best strategy for each hotel in the medium-term. The empirical application presented in this study, based on two similar hotels with a comparable demand located in different areas of the same destination, led to the following findings: (1) The elasticity values displayed by both hotels indicate that demands are not so inelastic as those values gathered in the hotel demand literature show; (2) In practice, the two hotels have completely different elasticity patterns during peak season and an awareness of these values could lead to changes in their shared early booking strategy; meanwhile in the low season, demand is quite inelastic for both hotels; (3) In the same way, the early booking strategy is proportionally constant throughout the season, while elasticity values are very different in low and peak season; therefore, setting different early bookings offers during the seasons and among hotels is highly recommendable; (4) The *RM Price* can be considered as a proxy for the *Real Price*; and (5) Knowing own-price elasticity values from past seasons can also have an impact on the long- to medium-term pricing

strategy since it can help to answer important questions such as: Is there an homogenous demand for the defined seasonal stay periods where prices remain constant or should an alternative period be defined? Have prices been correctly set in the price *Contract information* to fit in with hotel strategy?

In summary, the demand model is useful in defining the best pricing policy at the short-run that allows the revenue maximization (tactical price optimization), as well as in the definition of an appropriate pricing strategy (medium and long-run pricing) for online transient demand in the resort hotel sector. Additionally, the demand model can be easily replicable for other hotels of the resort segment.

Further research will focus on the model adaptation and estimation to other type of hotels, as well as to hotels located in different destinations, in order to test different seasonal and booking behaviour effects which are measured in elasticity terms as a basic and comparable unit. Other research could focus on partial demand function estimations. The main argument for this would be that new booking data from a new season could be introduced into a demand model before the date of stay takes place and the elasticity obtained would be the price elasticity of demand of the reservations that have taken place until that specific booking date. When that estimation is carried out regularly, as the booking horizon goes on, the elasticities obtained would be similar to those obtained in a dynamic model.

One limitation in our study is that additional data from the hotel or competitor prices possibly could be included to improve elasticity estimations. Taking into account additional hotel booking information –such as number of guests, room type, board, etc.–, as well other segment data –such as TO demand– could allow the original own-price elasticity to be split into different elasticity values, i.e., one elasticity for each of the heterogeneous demand segments to be considered. However, estimations using joint TO and online reservation data carry certain problems due to different underlying pricing objectives and strategies. In the case of TOs, prices and/or occupancy levels are set and agreed upon in long-term contracts between both parties (Aguiló et al., 2003 negotiations normally take place about one year in advance), while the online segment may have higher short-run price variation flexibility. In this sense, TO elasticities could be estimated in a similar model and compared with the online values in order to establish the best common pricing strategy for a specific hotel. Despite the hotel sector's greater potential for differentiation than the airline sector, and its subsequent impact on pricing (Lee, 2011; Lee et al., 2011), competitor price information is another source of a demand model improvement. Indeed, competition plays a particularly important role in customer choice RM models (Pachon et al., 2007; Perakis & Sood, 2004; Rattliff et al., 2008) and in some dynamic models relating to the hotel sector (Bayoumi et al., 2013).

2.7 Bibliography

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Chapter 3. Optimal Pricing for Online Hotel Demand

Abstract

Purpose - The online customer behavior in terms of price elasticity of demand and the effect of time along the booking horizon are placed as key requirements for the price optimization process that allows hotels to maximize their revenues. The seasonality and variability of prices present in the resort hotels, in combination with the lack of development of optimal pricing (OP) models in this specific segment, places the subject in an interesting field of study.

Design/methodology/approach - This study adapts the online transient hotel demand functions to deterministic and stochastic dynamic models—two extended OP methods existing in the literature—in order to determine the prices that maximize the revenues of two resort hotels.

Findings - (1) the stochastic estimations are usually more similar to the latest observed data, while the deterministic models produce more similar estimations to the average data; (2) not only the elasticity price of demand distribution across the booking horizon and the seasonality affect optimal prices, but also the hotel size, the location, and the tourist profile significantly affect optimal prices; (3) higher levels in demand elasticities generally produce lower levels of price estimations; and (4) the distribution of elasticities across the booking horizon and the natural variability of demand have an impact on OP.

Originality/value - The present paper adapts and applies two widespread revenue maximization models used in the literature to the hotel resort segment, and provides recommendations for designing pricing strategies for the online demand of resort hotels.

Key words

Price elasticity of demand, demand, booking horizon, optimal pricing, dynamic pricing, deterministic model, stochastic model

3.1. Introduction

In recent years, the study of pricing techniques has become a popular field of research in hotel revenue management (RM) literature. Legohérel et al. (2013) and Ivanov & Zhechev (2012) define RM as the application of information system control and pricing that allows for revenue maximization via the allocation of the right capacity at the right time in the right place. Cross et al. (2011) point out that RM has helped many companies increase their profits, as they are able to sell a relatively homogeneous product at different prices to different types of customers. The perishability of the hotel product, in conjunction with the capacity limitations of hotel establishments as well as seasonality, make demand management a crucial factor in the revenue maximization process (Coenders et al., 2003; Ivanov & Zhechev, 2012). Demand

management is especially relevant in the short run, due to the impossibility of changing the number of rooms during this period (Coenders et al., 2003). Price variations enable the revenue manager to adjust demand to the desired occupancy levels at any point along the booking horizon which leads to revenue maximization at the date of stay. In the hotel sector the most common way to segment customers is to set different prices according to tourist booking behaviors (Hanks et al., 2002). The reason for limiting the number of rooms to be sold at any moment on the booking horizon is based on the expectation that they will be sold in the future to a more profitable demand (Aziz et al., 2011). Thus, pricing represents a key tool in hotel RM (Cheng et al., 2011).

When focusing on the resort hotel sector, we have to consider that the sector usually combines two types of demands: the online transient segment, which is growing in importance, with the traditional Tour Operators' (TO) demand. For every season the hotel managers negotiate and decide first the number of rooms to allocate to the TO's demand (then the TO packages the hotel with other tourism products and sells it to the tourists), and then they allocate the rest of rooms to the online demand. In fact, the online transient segment is the only one directly managed and able to be changed at the short-run by hotel revenue managers, and pricing decision process is usually based on historical data and intuition, sometimes without directly considering the demand booking behavior.

Theoretically, the evolution of revenue maximization models in the hotel sector starts with room inventory control and evolves into the specification of complex customer behavior methods (Cross et al., 2009, 2011; O'Neill & Mattila, 2006). There are two popular models used in the literature, the first type is the deterministic dynamic pricing model which is used to discriminate prices across the booking horizon, thus allowing for revenue maximization (Aziz et al., 2011; Guadix et al., 2010; Lee, 2011). The second type is the stochastic dynamic model, mainly a consumer choice framework which segments the demand into different classes; every class is individually measured, as they are interrelated, and the objective is the determination of market responses to price variations (Jacobs et al., 2010; Pachon et al., 2007; Ratliff et al., 2008; Suzuki et al., 2001; Talluri & Ryzin, 2004a; Vinod et al., 2009).

In this paper we propose an application of two types of optimal pricing (OP) models for online transient demand that allows for revenue maximization at the hotel level, one deterministic model and another stochastic model, i.e., the two popular models mentioned before. These two models consider the demand response to price variation, as well as the seasonal and the booking date effects. On one hand, the optimal hotel prices between the peak and low season are significantly affected by demand variability (Abrate & Viglia, 2016; Gallego & Ryzin, 1994; Pan, 2007). In this sense, Coenders et al. (2003) and Juaneda et al. (2011) find that resort hotel prices can double during the peak season. On the other hand, the reservation time is one of the most common ways of practicing price discrimination in RM: the limited capacity of a hotel establishment and the expectations of selling the same room at a higher price at a later moment are the reasons for limiting room sales across the booking horizon (Aziz et al., 2011; Badinelli, 2000).

The first step in the revenue maximization process is the measurement of the market reactions to price variations, i.e., the demand function estimations (Lee, 2011; Desiraju & Shugan, 1999; Shy, 2008). In order to maximize revenue in this case we use a demand model that measures the own-price elasticity values under different seasonal demands and across booking horizons. The availability of the different seasonal price demand elasticities, as well as the effect of time along the booking horizon, represents the basis for defining the best OP methodology.

The present paper has two main objectives: (1) to adapt and apply the two widespread revenue maximization models used in the literature to the hotel resort segment, i.e., the deterministic and stochastic dynamic pricing models; and (2) to provide an empirical comparison of both models for the emerging online transient segment using data from two resort hotels located in Majorca, which could be useful to answer relevant questions for the island's resort sector such as: which type of model is more effective in optimizing the resort hotel's revenue?; how do the different values taken by the price elasticity of demand affect seasonal and booking horizon optimal prices?; how do the hotels' characteristics and specific demand behavior affect the estimations of optimal prices and revenues?; which effects may have limitations on the number of rooms allocated to the online transient segment?⁵; and what are the effects of the discounts offered along the booking horizon?

OP models and their empirical testing are quite extended in the airline sector, they are also quite common in the urban hotel sector, but as we pointed out before, their application in the resort hotel sector is more limited. The OP models developed in this paper are easily adaptable and replicable for the rest of resort hotels due to their characteristics—the wide range of seasonal effects and the variability of prices due to the different types of rooms and board pricing schemes (Cross et al., 2009). The application and testing of these models in the hotel revenue sector could represent a step towards the introduction of OP techniques in the resort segment, as we do not only present an OP model that allows the hotel's revenue maximization focused on the online transient demand, but we also test them in a broad range of situations with the empirical application of these models. The structure of this paper is organized as follows. After the introduction, section 2 presents a literature review focused on OP and revenue maximization. Section 3 describes the methodology, i.e., the demand model used and the two different price optimization models analyzed. Section 4 details the data used from two resort hotels in Majorca. Section 5 outlines the results of the estimation of optimal prices, sales, and revenues; finally, in section 6, we discuss the implications of the results in terms of OP.

3.2 Literature Review

⁵ The Majorca resort hotels usually combine the online transient demand, which has gained considerable interest during the last years, with the TO's demand, which still accounts for 55% of tourists travelling to Majorca (CAIB, 2017). In the online transient segment half of the bookings usually take place during the last three months before the date of stay, while in the TO's segment prices and occupancy levels are usually negotiated with TOs one year in advance (Aguiló et al., 2003), then they pack and sell the tourist products.

Classical modeling of hotel revenue maximization focuses on optimal allocation (Aziz et al., 2011). Optimal allocation means selling the right amount of inventory at a given price, where each of these prices is associated with one of various previously identified classes/segments (Desiraju & Shugan, 1999; El Gayar et al., 2011; Pan, 2007). However, more complex models are associated with differences in the customers' willingness to pay as the date of stay approaches. So, problems arise when trying to set a pricing policy that is able to maximize the company's revenue, while considering the sensitivity of demand to price variations (Aziz et al., 2011; Badinelli, 2000). These models are called dynamic pricing models, and they maximize revenue by offering a price that reflects current demand and hotel occupancy levels (Ivanov & Zhechev, 2012), while considering different customer behaviors along the booking horizon. The dynamic models are mainly used to deal with the trade-off between selling a room today and waiting for an expected higher price that a potential customer will pay in the future (Chatwin, 2000; Guadix et al., 2010). In practical terms, Aziz et al. (2011) highlight the advantages of dynamic pricing models as different price segments for each overnight stay are considered. In order to maximize revenues, they set different price categories along the booking horizon as well as allow for the introduction of dynamic changes when a new reservation takes place. Ratliff et al. (2008) point out that dynamic models vary as a function of time along the booking horizon. Thus, the time before the date of stay plays a key role in price determination.

In that sense, a direct and common way to typify customer behavior is through a demand function, which is able to reflect the consumers' willingness to pay (Shy, 2008). The main demand models used in the literature that reflect how sales/bookings are changing as prices change are the following: (1) linear demand functions (Guo et al. 2013; Lee, 2011; Shy, 2008; Suzuki et al., 2001); (2) non-linear demand functions, such as a Cobb-Douglas demand function (Guo et al. 2013; Lee, 2011; Shy, 2008; Suzuki et al., 2001), which can be linearized; and (3) customer choice demand models, mainly multinomial logit (MNL) (Akçay, et al., 2010; Pachon, 2007; Ratliff, 2008; Talluri and van Ryzin, 2004a). The demand function estimation is a powerful tool in revenue maximization as demand changes can be measured under different price structures and market conditions (Lee, 2011; Lee et al., 2011). In the hotel sector, Hormby et al. (2010) use the demand modeling in order to segment the demand based on the hypothesis that customer sensitivity varies depending on variables such as the booking date, group size, and season. Lee (2011) in order to assess the linear demand models in different hotel typologies –airport, suburban, and urban hotels– uses the following variables: prices, reservation date, length of stay, and the weekday of arrival. Aziz et al. (2011) estimate the demand with a probit function. Bayoumi et al. (2013) use an algorithm to calibrate the hotel elasticity with historical data. Guo et al. (2013) study the dynamic pricing strategy in the hotel sector through online market demand segmentation. They use two types of demand functions, linear and non-linear, and estimate the optimal number of market segments to be differentiated along the booking horizon that allow the revenue maximization. Thus, the literature usually describes the measurement of price elasticity of demand as a basic step in the bookings' estimation, which is linked with different price levels, and with other variables such as the seasonality or booking horizon date.

The OP dynamic models consider the willingness to pay as the date of stay approaches and allow the hotel revenue maximization; they can be classified into deterministic and stochastic or probabilistic approaches (Talluri & van Ryzin, 2004b). The deterministic models are more suitable when the sensitivity of customer varies along the booking time, while the stochastic models performs better with the random fluctuations of demand and the option of keeping capacity for the future instead of just selling units (Talluri & van Ryzin, 2004b; Zhang & Weatherford, 2016).

More specifically, the deterministic dynamic models allocate the hotel capacity according to the average demand along the booking horizon (Talluri & van Ryzin, 2004b). Guadix et al. (2010) point out that the deterministic models try to anticipate the price elasticity of each demand segment that allows the hotel revenue maximization. In practical terms, Aziz et al. (2011) develop a dynamic pricing model that allows for hotel revenue maximization for each overnight stay. The model enables consumer segmentation through daily price variations, which are influenced by two main variables: (1) the time before the date of stay, which is a continuous variable along which consumer behavior changes; and (2) the hotel occupancy, i.e., changes in supply levels, so that the price can vary after a new booking. Guadix et al. (2010) attempt to anticipate the number of rooms that can be sold for a specific date of stay at a determined price by considering variables such as the length of stay, and the segmentation between transient customers and group customers. The model forecasts the price elasticity of demand and the expected sales that maximize the hotel revenue. Lee (2011) defines the hotel product as a combination of the following variables: the reservation's arrival date and the length of stay which are limited by the available capacity at this specific date. In her theoretical model the variable to be optimized is the hotel price, while the hotel demand is a negative function of price.

However, the stochastic nature of the tourism demand makes it never perfectly predictable, as the customers book the product before its consumption at the date of stay. Thus, the stochastic processes allow the anticipated demand to differ from the historical average demand levels (Badinelli, 2000; Guadix et al., 2010), where the customer only buys the product if its price is below his or her maximum willingness to pay (Chatwin, 2000; Zhao & Zheng, 2000). Several stochastic dynamic models specify the demand following a Poisson process as the booking horizon draws closer to the date of stay and the inventory diminishes. For example, Gallego & van Ryzin (1994) maximize revenue by using an OP model with a stochastic price-sensitive demand. When demand seasonally changes, they recommend a price policy that assigns appropriate fractions of time and capacities to each fare segment, so they consider booking time and occupancy variables. Similarly, Zhao & Zheng (2000) show that price changes are caused by statistical fluctuations in demand and changes in customers' willingness to pay along the booking horizon. Feng & Xiao (2000) use a model that allows for multiple price changes over the booking horizon when consider constant demand intensities. Chatwin (2000) argues that the intensity of demand depends on the price set by the seller. He finds that the lowest prices are set at the earliest dates across the booking horizon, and also when the hotel faces low levels of reservations. Sierag et al. (2015) and Talluri & van Ryzin (2004a) introduce cancellations in a

customer choice model. Sierag et al. (2015) find that the consideration of cancellations in the dynamic pricing process may lead to a revenue increase of a 20%.

More specifically, stochastic models consider that bookings are able to capture the variability in the customers' product valuation and perception, in terms of the probability of a product being available over time (Yilmaz et al., 2016). Thus, the stochastic models allow hotel rooms reservations different from the mean (historical data), by considering the natural variability of the demand (Guadix et al., 2010). Stochastic models capture customer choice probabilities and measure their utility based on the use of historical data (Akçay et al., 2010; Pachon, 2007; Ratliff, 2008; Talluri & Ryzin, 2004a). The interdependence of the different segments are considered by the customer choice models, these models are able to represent the heterogeneity of preferences of each segment, while they can also model uncertainty, as a large range of customer behaviors (Talluri & van Ryzin, 2004b). The stochastic models are also able to measure the cross-elasticities effects, these can involve price variations of a company within a market, a segment class within a product demand, a booking time along the booking horizon, and others. Most of them use multinomial logit (MNL) models, which consider that individual demands are affected by different known attributes, and so their effects influence consumer choices. Talluri & van Ryzin (2004a) tackle the MNL optimization problem of selecting a group of fare products to be offered at each point in time for a multi-fare class. The multi-fare class allows for the definition of multiple products at any point of the booking horizon. Therefore, the MNL model allows for the consideration of different variables such as the ability to be refunded, minimum length of stay, and other non-price factors, which are not properly captured by the deterministic models.

When deterministic and stochastic models are compared, Guadix et al. (2010) find that in those situations, when the demand is higher than the supply, the likelihood of a customer accepting higher prices is larger in the stochastic models. They find that the deterministic model obtains better results when analyzing the whole demand hotel behaviour. In terms of hotel dynamic pricing, Zhang & Weatherford (2016) highlight that the deterministic linear programming performs well when the different network effects are considered, i.e., the effects on demand and capacity caused by multiple lengths of stay, while the demand uncertainty is ignored. Meanwhile, the stochastic dynamic pricing formulation is able to solve the demand uncertainty, but the network effects are only captured through bid-prices and prices proration. Regarding the dynamic room allocation, Aydin & Birbil (2018) detect that the consideration of the stochastic nature of the demand and the network effect improve the bid price policies for advance bookings. When the authors also consider the stay-over room consumption, the stochastic models behave better as they consider the uncertainty of staying more nights beyond the reservation. On another hand, when the customer behavior is compared when facing a price increase or a price discount, Suzuki et al. (2001) use a logit model that considers variables such as the service quality and prices in the airline sector, they detect an asymmetric market response, and find a stronger market response to a price increase compared to a price reduction. Vinod et al. (2009) propose two strategies in the tariff structure of a competitive market: short-run (tactical) and long-run (strategic) airline fare optimization. While short-run pricing is

based on fare changes in response to actions by rival companies, which is directly related to the market share dimension, the objective of long-run pricing is to determine a new tariff structure, where different pricing objectives, business constraints, and more complex responses are set by competitors. Guizzardi et al. (2017) highlight that the consideration of the stochastic nature of hotel price trends along the booking horizon is usually not effective, due to the lack of price variability of urban hotels located in Italy. They also find that hotels do not usually adopt strategic planning of dynamic pricing trends for both, business and leisure segments. In this context, Oses et al. (2016) detect that most of the price changes across the booking horizon of hotels located in Bilbao correspond to competitors' price variation, demand fluctuation, and inventory changes, and just for 3-stars hotels and more dynamic pricing policies which are not caused by the previous factors can be found. Al-Shakhsheer et al. (2017) show that comprehensive dynamic pricing strategies and tactics in Jordanian hotels can improve room rates and occupancy, i.e., increase the hotel revenue. Cho et al. (2018) using US luxury-urban hotel database are able to predict the hotel pricing behavior in a dynamic way, as well as the level of bookings and cancellations using a stochastic model. They also observe that revenue managers follow the price competitors' trends, while they usually do not follow the RM system recommendations. Nevertheless, their results suggest that the pricing strategy followed is competitive, as the hotel considers the demand behavior and the competitors price levels in its decision process.

Finally, the available literature identifies some problems with OP models. For example, Badinelli (2000) identifies some problems sometimes historical demand data does not offer good predictions of the future and in those cases, real booking data would improve the estimations of future demand. Ratliff et al. (2008) also stress the problem of data availability: most of the time information is only available on the company studied. Meanwhile, the choice models focus on the market-level context. These problems can be mitigated by looking at long historical periods that incorporate the seasonal and booking horizon demand behavior. Additionally, current booking information can introduce demand behavior shifts which are not reflected in historical demand behavior.

3.3 Methodology

3.3.1 Demand model

As we pointed out in the literature review section, the demand function is a direct way for measuring the customer behavior in the hotel reservation process. In that specific case, the number of online transient bookings (Q_t^d) for a specific date of stay (d) is a function of the price set by the hotel (p_t^d) and the booking time (r_t^d), i.e. the distance between the date of stay and the booking date.

$$Q_t^d = f(p_t^d, r_t^d) \quad (1)$$

Where: $t = 1, 2, \dots, d$.

The time t represents the date along the booking horizon, where d represents the date of stay, i.e., the last observation across the booking horizon.

The demand function can be specified by a linear formulation (2) or a linearized Cobb-Douglas formulation which can be linearized with the application of natural logarithms (3) (Guo et al. 2013; Suzuki et al., 2001).⁶

$$Q_t^d = \alpha_0 + Dummies + \alpha_p \cdot p_t^d + \alpha_r \cdot r_t^d \quad (2)$$

$$\ln Q_t^d = \beta_0 + Dummies + \beta_p \cdot \ln p_t^d + \beta_r \cdot \ln r_t^d \quad (3)$$

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

The b factor is the booking period, usually grouped by month or half a month, depending on the moment along the booking horizon—normally the dates closer to the date of stay require more observations due to the booking activity. The y factor represents the year when the observation takes place.

Finally, dummy variables are used for modelling the booking time and date of stay variables. More specifically, the dummy Dy represents the year of the date of the stay and takes the value 1 when the observation pertains to a specific year and 0 otherwise (yy), as we are working with historical booking data from different years. The booking period (Db) takes the value 1 when the observation pertains to a specific period of time across the booking horizon and 0 otherwise (mm). The date of stay (Dd) takes the value 1 when the observation pertains to a specific date of stay and 0 otherwise (d), which is the last observation along the booking horizon. Here below there is an example of dummies distribution, the historical data corresponding to three years or seasons (2014-16 - Dy) that are used to estimate the demand function; while the booking period are grouped in homogenous intervals, specifically in a month or half a month (Db), which depends on the time before the date of stay; finally, as homogenous periods of stay are grouped in the same demand function, the specific dates of stay are specified by the Dd .

⁶ Although the Translog production function is more flexible compared with the Cobb-Douglas demand function, in our specific application the second demand function presents less correlation problems between the reservation times along the booking horizon and the prices.

$t = yy-01-01, yy-01-02, \dots, yy-01-31, \dots, yy-mm-D; yy+1-Jan-01, \dots, yy+1-mm-D$

$t = \underbrace{1, 2, \dots, 31, \dots, d}_{1, \dots, mm}; \quad \underbrace{1, \dots, d}_{1, \dots, mm}$
 $D_b = \underbrace{\hspace{10em}}_{yy}; \quad \underbrace{\hspace{10em}}_{yy+1}$
 $D_y = \hspace{10em}$

$D_d = 1, 2, \dots, D$

The following step is the transformation of the equation (2) of the daily room reservations (Q) into the average number of daily room reservations (q) for each period of time when the p remains constant along the booking horizon.

$t = 1, 2, \dots, d$
 $\underbrace{\hspace{2em}}_{t'_1 = p_1} \quad \underbrace{\hspace{2em}}_{t'_2 = p_2} \quad \dots \quad \underbrace{\hspace{2em}}_{t'_m = p_m}$

$$\ln q_{t'}^d = \beta_0 + Dummies_{y,d,bp} + \beta_p \cdot \ln p_{t'}^d + \beta_{RES} \cdot \ln r_{t'}^d \quad (4)$$

where: $Q_{t'} = q_{t'} \cdot t'$

In this case, t' represents the number of days p remains unaltered. More specifically, d represents the date of stay and t' are booking periods leading up to d , which are variable in length.

3.3.2 Price optimization – deterministic model

The representation of the revenue maximization model (R) is quite common in the optimal pricing literature (Aziz et al., 2011; Badinelli, 2000; Guadix et al., 2010; Lee, 2011):

$$R(t') = \mathbf{Max} \sum_{t'} Q_{t'}^d \cdot p_{t'}^d \quad (5)$$

Thus, with the number of online transient reservations ($Q_{t'}^d$) multiplied by the price ($p_{t'}^d$) we can obtain the number of average daily room reservations ($q_{t'}$) that t' maximizes the revenue obtained along the booking horizon t' and for each date of stay d .

Before this, we must transform the demand function in order to isolate the price variable, which allows the optimization to be performed over one variable ($q_{t'}$).

$$-\beta_p \cdot \ln p_{t'}^d = \ln q_{t'}^d - \beta_0 - Dummies_{y,d,b} - \beta_r \cdot \ln r_{t'}^d$$

$$e^{\ln p_{t'}^d} = e^{\frac{\ln q_{t'}^d - \beta_0 - Dummies_{y,d,b} - \beta_r \cdot \ln r_{t'}^d}{-\beta_p}}$$

$$f(q_{t'}^d, r_{t'}^d) \rightarrow p_{t'}^d = e^{\frac{\ln q_{t'}^d - \beta_0 - \text{Dummies}_{y,d,b} - \beta_r \cdot \ln r_{t'}^d}{-\beta_p}} \quad (6)$$

In order to simplify the notation, we are going to work with only one date of stay. Additionally, two different demand functions are used as defined in Vives et al. (2018a), where they detect two differentiated demand behaviors along the booking horizon for the same dates of stay; therefore, as t' varies as the date of stay approaches, it is possible to distinguish two different demand functions $f(p_{1,t'}, r_{1,t'})$ and $f(p_{2,t'}, r_{2,t'})$.

$$\mathbf{Max} R(t') = \sum_{1,t'} Q_{1,t'} \cdot f(q_{1,t'}, r_{1,t'}) + \sum_{2,t'} Q_{2,t'} \cdot f(q_{2,t'}, r_{2,t'}) \quad (7)$$

$$\mathbf{s.t. (1)} \quad \lambda_1: \sum_{1,t'} Q_{1,t'} + \sum_{2,t'} Q_{2,t'} \leq r$$

$$\mathbf{s.t. (2)} \quad \lambda_2: p_{1,1} \leq p_{1,2} \leq \dots \leq p_{1,n-1} \leq p_{1,n} \leq p_{2,n+1} \leq \dots \leq p_{2,d-1} \leq p_{2,d} = f(q_{1,1}, r_{1,1}) \leq f(q_{1,2}, r_{1,2}) \leq \dots \leq f(q_{1,n}, r_{1,n}) \leq f(q_{2,n+1}, r_{2,n+1}) \leq \dots \leq f(q_{2,d}, r_{2,d}) \quad \forall t'$$

where: $n \leq d$

The Lagrange multiplier method is used in order to estimate the prices and bookings along the booking horizon that maximize the revenue, which is subject to the number of rooms r the revenue manager is willing to sell (s.t. 1); the maximum number of rooms that can be sold is the hotel capacity. Vives et al. (2018a) group hotel sales into two groups, one for online sales and the other for tour operator sales, the tour operator sales are negotiated a long time in advance, while the online sales take place in the short-run context. Thus, both types of demand are not compatible with each other in the same dynamic model, and the number of rooms allocated for each segment can vary across the different dates of stay, i.e., the managers first decide the capacity to be allocated to the TO segment and the rest of capacity is assigned to the online transient segment. While the second constraint (s.t. 2) is an optional pricing policy defined by the revenue managers; they want to know the optimal price that can be set at every moment without the possibility of decreasing prices along the booking horizon policy.

$$\mathbf{L(1)}(q_{1,1}, q_{1,2}, \dots, q_{1,n-1}, q_{1,n}, q_{2,n+1}, \dots, q_{2,d}, \lambda_1) \quad (8)$$

$$\mathbf{L(2)}(q_{1,1}, q_{1,2}, \dots, q_{1,n-1}, q_{1,n}, q_{2,n+1}, \dots, q_{2,d}, \lambda_1, \lambda_2) \quad (9)$$

The final output is the optimal price for each moment of time for each of the predefined periods of time t' for each demand function. Every price ($p_{t'}$) is directly linked to the average number of daily room reservations ($q_{t'}$) that maximizes revenues, subject to the number of rooms available.

3.3.3 Price optimization – stochastic model

The stochastic models in the hotel OP reports a utility that is associated with a probability of sales, usually MNL models (Ratliff et al., 2008; Talluri & van Ryzin, 2004a), and the objective is the utility maximization of each alternative (Anderson & Xie, 2016). In our case it would be the probability that takes place in each period along the booking horizon. Nevertheless, the dependent variable ($Q_{t'}$) in our demand function (1) takes nonnegative integers. Therefore, the Poisson regression is more suitable as the hotel reservations are an observed count and follow a Poisson distribution as pointed out by several authors (Chatwin, 2000; Feng & Xiao, 2000; Gallego & van Ryzin, 1994; Zhao & Zheng, 2000). The Poisson regression is a stochastic model with some similarities to a logistic regression and containing a discrete explanatory variable. In the same way, Wang et al. (2015) indicate that a multi-variable linear regression is not a suitable model for estimating the hotel booking as it is not normally distributed. They highlight that the Poisson regression model is more appropriate as it is a discrete variable. Chaiboonsri & Chaitip (2012), Chen et al. (2011), and Karimi et al. (2015) also use a Poisson regression model to forecast aggregate international tourism demand.

In the Poisson regression model the expected value of the dependent variable, bookings ($Q_{t'}$), is denoted by $E(Q_{t'}) = \mu_{t'}$

Where the probability (Pr) of the Poisson regression model in the booking moment t' is drawn from Chen et al. (2011):

$$\Pr(\text{Bookings}_{t'} = Q_{t'}) = \frac{e^{-\mu_{t'}} \mu_{t'}^{Q_{t'}}}{Q_{t'}!} \quad (Q_{t'} = 0, 1, 2, \dots) \quad (10)$$

The Poisson is a log-linear model:

$$\log \mu_{t'} = f(p_{t'}, r_{t'}) \quad (11)$$

$$\mu_{t'} = e^{f(p_{t'}, r_{t'})} \quad (12)$$

Again a revenue maximization model (R) with the Lagrange multiplier method is used, similar to the deterministic model:

$$R(t') = \text{Max} \sum_{t'} p_{t'} \cdot e^{f(p_{t'}, r_{t'})} \quad (13)$$

$$\text{s.t. (1)} \quad \lambda_1: \sum_{1,t'} Q_{1,t'} + \sum_{2,t'} Q_{2,t'} \leq r$$

$$\text{s.t. (2)} \quad \lambda_2: p_{1,1} \leq p_{1,2} \leq \dots \leq p_{1,n-1} \leq p_{1,n} \leq p_{2,n+1} \leq \dots \leq p_{2,d-1} \leq p_{2,d}$$

And again the two demand behaviors are introduced in the maximization process:

$$R(t') = \text{Max} \sum_{1,t'} p_{1,t'} \cdot e^{f(p_{1,t'}, r_{1,t'})} + \sum_{2,t'} p_{2,t'} \cdot e^{f(p_{2,t'}, r_{2,t'})} \quad (14)$$

3.4 Data

The present study uses data on the online transient segment from two 4-star Majorcan hotels belonging to one of the top four multinational hotel chains in the Balearic Islands. Regarding the hotel chain information, it annually sets individual hotel prices which vary according to the seasonal period of stay, type of room, type of board, guest type, booking date, length of stay, and method of payment. The highest prices are found during July and August, the peak season, and they are 115-120% higher than those from the low season, and account for around 35-41% of the yearly reservations. Concurrently, 32-41% of bookings take place during the peak season, when a 31.5% of international tourist arrivals to Majorca's airport concentrate (CAIB, 2016). Regarding the price evolution across the booking horizon, each hotel sets three predetermined early booking periods offering discounts of between 5% and 15% depending on the specific date. Then, the revenue manager is able to alter prices along the booking horizon according to the booking date, number of reservations, and occupancy level.

Regarding the hotels' characteristics, Hotel 1 has 619 rooms, and almost 33% of the reservations are made online (the majority sold in Booking.com, Expedia, and the own-hotel chain web page). Hotel 2 has 366 rooms, and slightly more than 35% of the reservations are made online. During the last few years the growth of the online segment has been substantial in both hotels. Hotel 2 is located in a very popular and highly transited area of Majorca, with more than twice as many beds as the area in which Hotel 1 is located (CAIB, 2015). Regarding the tourist profile, the demand for Hotel 1 comes mainly from Germany and Spain. Most of the tourists are families, 90% of reservations are made with all-inclusive board, and the length of stay averages almost 7.5 days. The demand for Hotel 2 mainly comes from the German and English markets. Most of the tourists are couples, only 50% of reservations are made with all-inclusive board, and the length of stay is 8 days on average.

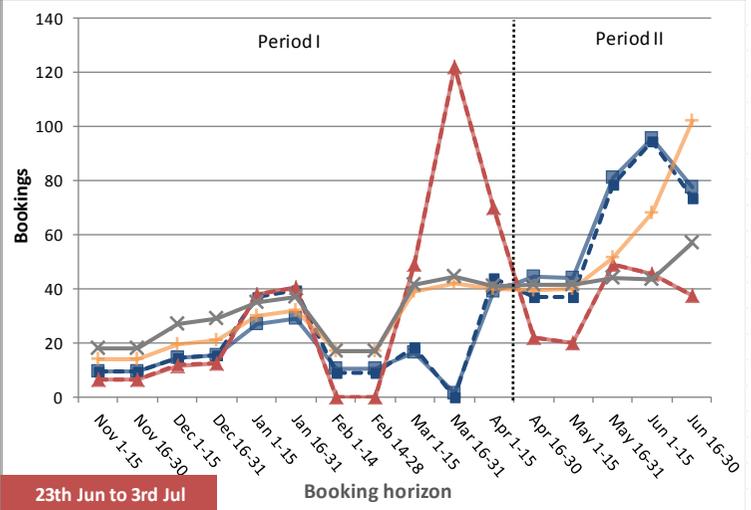
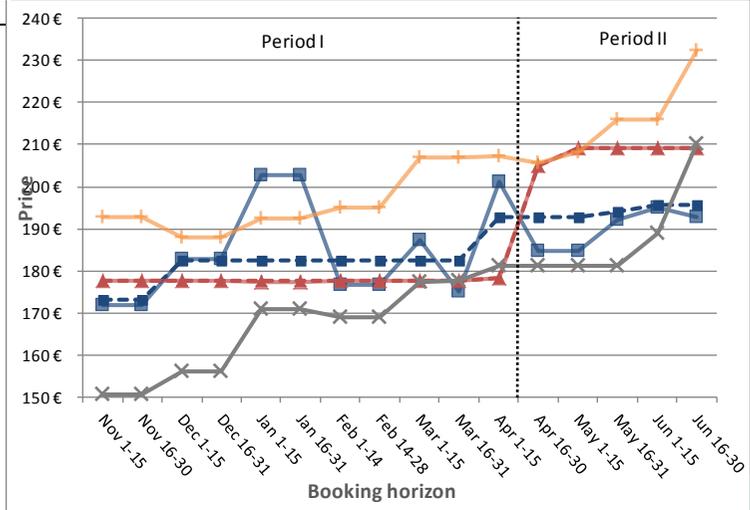
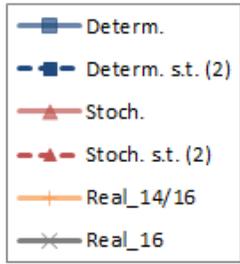
The hotel chain supplied all of the information necessary for obtaining the different demand functions: the daily room reservations (Q_t); daily prices (P_t). The dates of stay are grouped into homogeneous dates of stay (periods between 9 and 28 days): the dates farther from the dates of stay where the reservations' pace and prices are low (period I) and the dates closer to the dates of stay where the level of bookings and prices significantly increase (period II); in each of these two periods approximately half of the rooms are booked. Finally, each of these groups of dates of stay are divided in two differentiated demands functions, which are used in the revenue maximization methodologies, due to the two differentiated booking behaviors found by Vives et al. (2018b).

3.5 Results

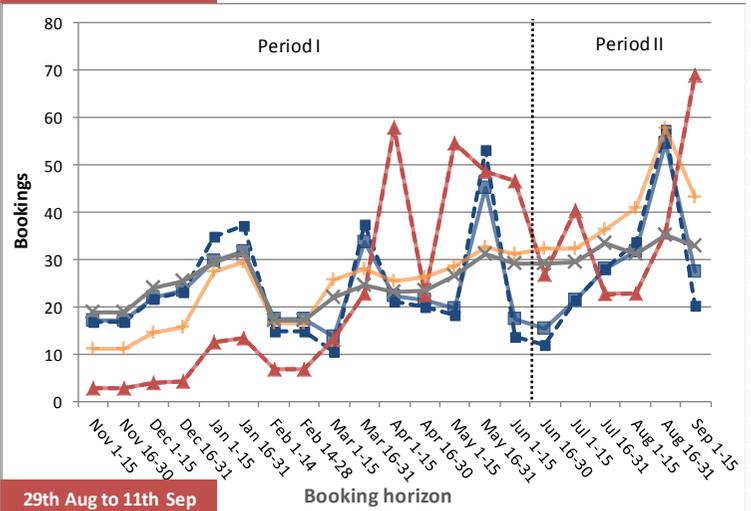
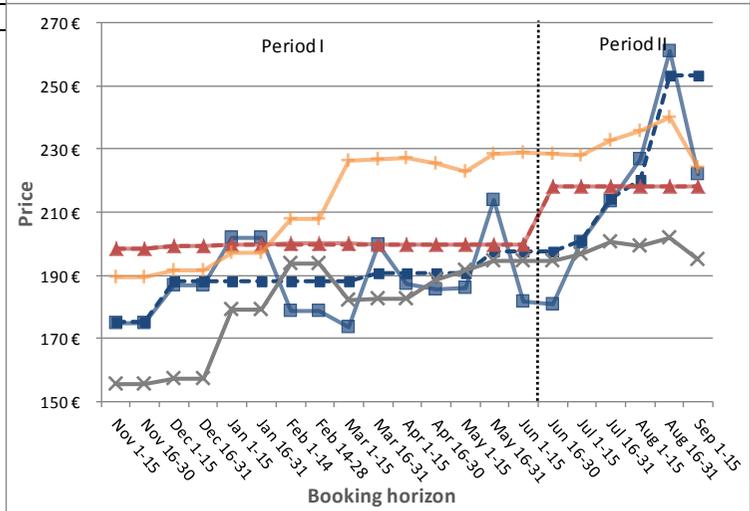
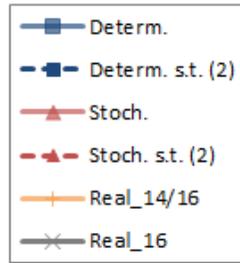
In this section we present some illustrative examples from all of the cases obtained in our study. Firstly, *Figure 1* and *Figure 2* present two estimations examples from both hotels' optimal prices, daily number of room reservations from online transient demand, and elasticities, as well as the observed prices and reservations for the season 2016 and the average from the last three seasons (2014-16). Four different

Figure 1. Hotel 1's seasonal optimal prices, daily number of room reservations, and elasticities (estimated and observed) Example

Dates of stay: 23th Jun to 3rd Jul	
Period I	-2.73 -4.32
Period II	-1.31 -2.24

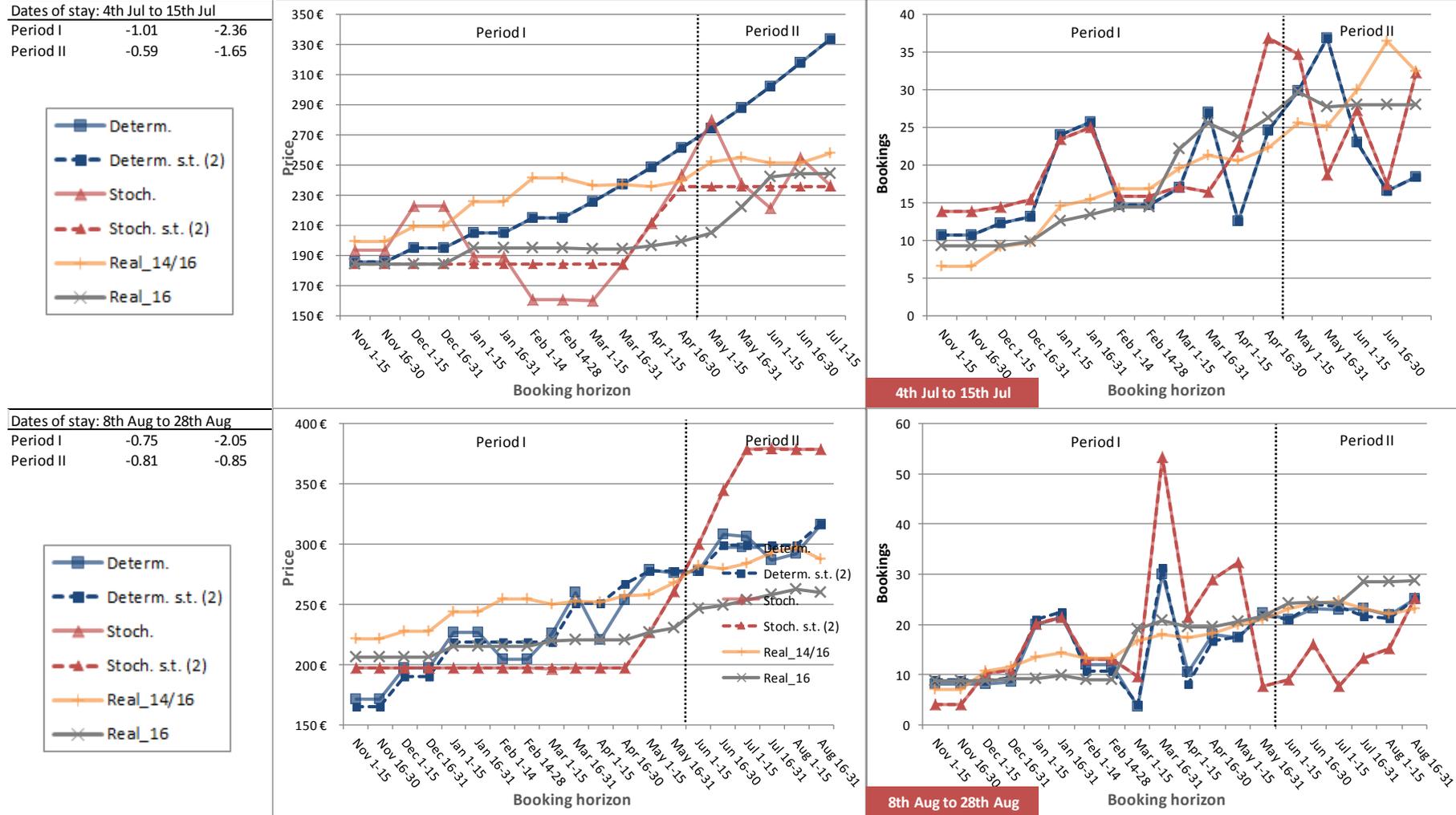


Dates of stay: 29th Aug to 11th Sep	
Period I	-0.78 -1.26
Period II	-0.83 -1.26



Source: Own elaboration

Figure 2. Hotel 2's seasonal optimal prices, daily number of room reservations, and elasticities (estimated and observed) Example



Source: Own elaboration

estimations are presented: the deterministic and stochastic models subject only to the first constraint, the limitation in the number of rooms (s.t. 1), and both models again but subject to the limitation in number of room (s.t. 1) plus the policy of not decreasing prices across the booking horizon (s.t. 2).

In general, the deterministic dynamic model present larger levels of price variability, but lower levels of variability in bookings compared to the stochastic model (Figure 1 and Figure 2). Thus, the Figures 1 and 2 show that the estimated reservations across the booking horizon of the stochastic model are more irregular. However, the price levels are usually higher in the deterministic model, and the trend that they follow are more similar to the average prices when the last three seasons (2014-16) are considered; while the prices in the stochastic model are lower, and present more similarities to the prices of the last season (2016). The main reasons for these outcomes are explained by the fact that the deterministic dynamic models estimate the bookings according to the average demand of the historical data (Talluri & van Ryzin, 2004b), while the stochastic models allow the estimations of bookings different from the average demand, by allowing the natural variability of demand (Guadix et al., 2010). Similarly Guadix et al. (2010) results indicate that the deterministic models obtain better estimations in terms of revenue.

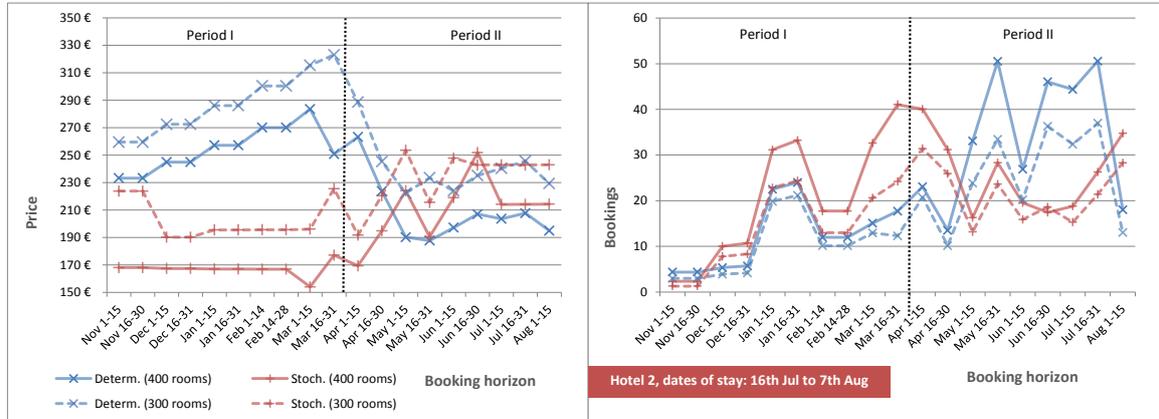
In general terms, both models present lower levels of reservations on the earliest booking dates, and they increase as the date of stay approaches, while the prices were always higher on average during period II (Aziz et al., 2011; Desiraju & Shugan, 1999). Furthermore, the second constraint in the model (i.e., s.t. 2 limitation, which does not allow for prices to decrease along the booking horizon) led to maintenance or reduction of prices in the maximization processes depending on the elasticities disposition across the booking horizon and their values, in general the behavior is similar in both types of models.

When comparing the elasticities of both hotels with their specific booking and prices levels across the booking horizon, it is clear that none of these factors is directly related with the differential pricing. The pricing differences are also explained by the specific booking characteristics, the type of tourist, and the hotel location. Nevertheless, higher levels of demand elasticities usually produce lower levels of prices in the models' estimations, in the same way as observed by Perakis & Sood (2004).

In terms of revenue projections from both models, which are obtained by multiplying the price and booking estimations, we can say that on average the deterministic model provides revenues 14.1% higher than the observed revenues from the last season (2016) in Hotel 1, and a 14.7% higher in Hotel 2; while the stochastic model provides revenues a 3.1% higher in Hotel 1, and a 0.4% higher in Hotel 2. Thus, the price and booking forecasts of the deterministic framework is more optimistic compared with the stochastic one, where forecasts are closer to the observed revenues from the last season.

Secondly, what happens when the number of rooms available for booking in a specific hotel is limited? Figure 2 shows the result of Hotel 2 expanding the availability of rooms to 425 instead of 325 (Figure 3).

Figure 3. Hotel 2s optimal prices, daily number of room reservations, and elasticities (300 rooms vs. 400 rooms). Dates of stay: 16th July to 7th August.



Source: Own elaboration.

Pan (2007) points out that a higher hotel capacity negatively affects optimal prices, while Perakis & Sood (2004) observe that prices are lower for a larger inventory level for the whole booking horizon. We also observed similar results when analyzing the information from Figure 3, where the increase of room availability led to lower levels of prices. The increase in number of rooms finally led to lower levels of revenue raise compared to the growth in room availability. In the maximization model estimations from Figure 3 when the number of rooms available were increased by 30%, the optimal level of prices decreased on average by 14%, while the total revenue increased only by 12.5%. Nevertheless, when comparing the prices of both hotels, Hotel 1 presents higher levels of prices despite having much larger capacity, as we point out before this is caused by the differences from the specific booking characteristics, the type of tourist, and the hotel location.

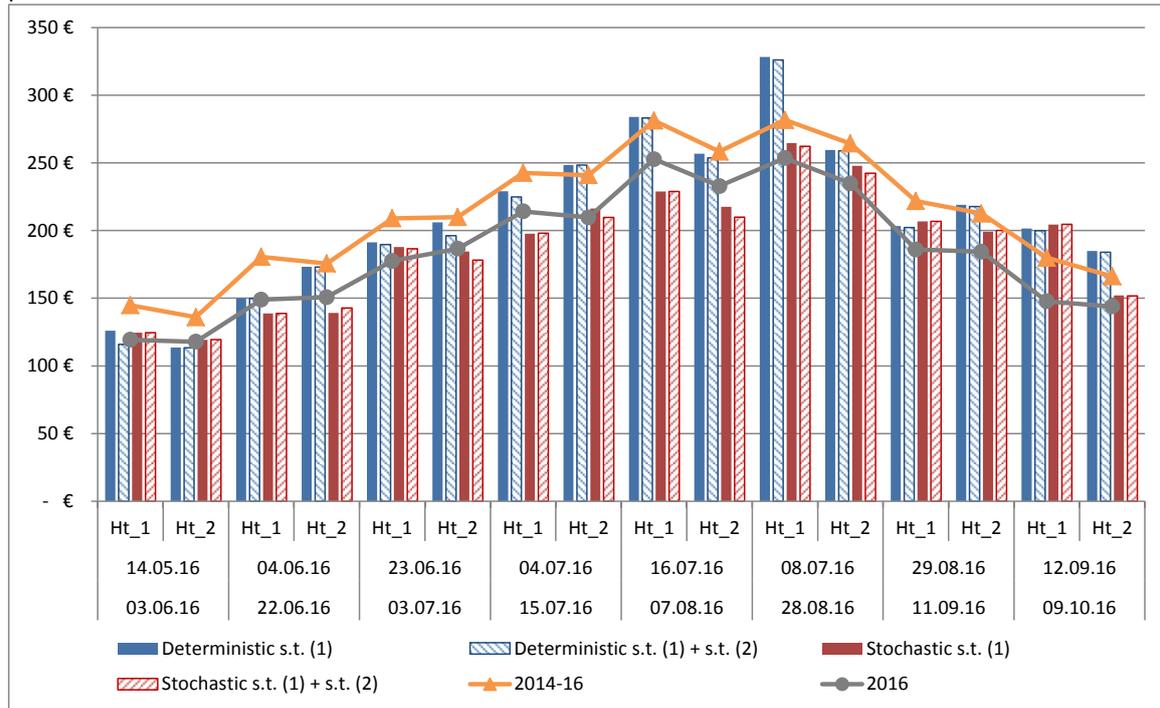
Thirdly, what happens when the seasonal estimations from the two different hotels are compared? The results can be seen in Figure 4. The hotel location, hotel size, and the tourist profile were other factors that affected the OP that allowed for revenue maximization. Hotel 2 has a considerably lower capacity than Hotel 1. It is located in a more popular area, and as we mentioned in the previous section, there are differences in the tourist profile.

Considering that Hotel 2 offers online more or less half the number of rooms than are being offered by Hotel 1, when comparing the estimations for both hotels (Figure 4), the results indicate that in the maximization process Hotel 1 set prices between a 3% and a 6% higher and earned between a 63% and a 73% more revenue, depending on the type of model estimation used (deterministic or stochastic) and on the observed price.⁷ In this sense, Aguiló et al. (2001), Aguiló et al. (2003), Espinet et al. (2003),

⁷ On average the deterministic model estimates a price only a 3% higher for Hotel 1 than for Hotel 2, while the stochastic model sets a price 6% higher, however both models estimate revenues 65% higher

Juaneda et al. (2011), and Papatheodorou (2002) support the hypothesis that a hotel resort’s location is a source of price variability. Additionally, Balaguer & Pernías (2013), Pan (2007), Thrane (2005), and White & Milligan (2002) point out that hotel capacity is another cause of price variability. Finally, hotel booking options such as the type of board (Aguiló et al., 2001; Juaneda et al., 2011; Lee & Jang, 2011; Papatheodorou, 2002; Thrane, 2005) or free cancellation policies (Abrate et al., 2011), or tourist nationality (Abrate et al., 2011) also affect OP.

Figure 4. Comparison of seasonal average prices from Hotel 1 and Hotel 2, estimations and observed prices.



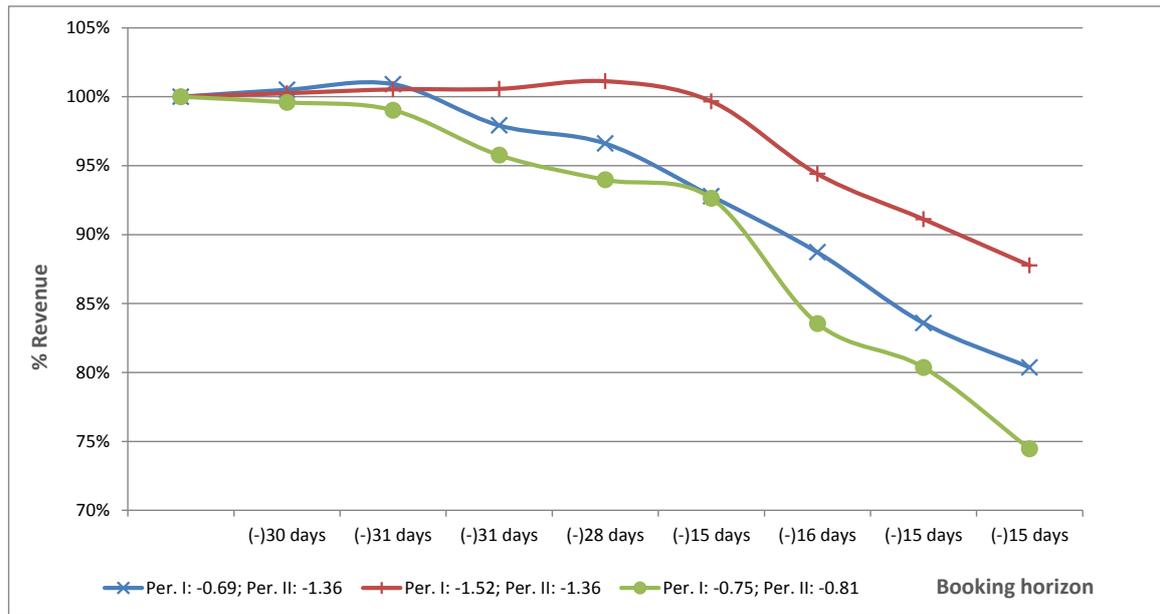
Source: Own elaboration.

When comparing the seasonal prices (Figure 4), the peak season prices double the low season prices in both hotels. Additionally, during the peak season is when the differences between the observed and estimated prices are higher, especially in the case of Hotel 1. Juaneda et al. (2011) point out that the seasonality can be a source of price differences when considering different types of establishments. Equally, the deterministic model sets higher prices, especially during the peak season months, while the observed prices during the last season (2016) are lower compared with the average price of the three seasons.

Fourthly, what happens when the booking horizon is limited? Figure 5 shows an estimation of the revenue loss in the dynamic pricing maximization process due to booking horizon limitations, i.e., limiting the number of days before which a room can be booked for a certain date of stay. Three different scenarios under different elasticity values are considered.

for the first hotel –the observed prices are a 5% higher for the seasons 2014-16 and a 3.5% for the last season, while the revenues are a 73% (2014-16) and a 64% (2016) larger.

Figure 5. Expected change in revenue when the booking horizon is limited under different elasticity levels.



Source: Own elaboration.

Figure 5 shows that inelastic demand produces larger revenue reductions compared to elastic demands when the booking horizon is limited. This is due to the fact that via elastic demand, it is possible to alter reservation levels with small price variations, while with inelastic demand it is not possible to reach certain levels of occupation with low price variations.

Finally, we compared and analyzed a range of situations: the effect of various elasticity values on optimal prices and reservations across the booking horizon, i.e., period I—the earliest dates along the booking horizon—and period II—the dates closer to the date of stay.

In general terms, more inelastic demands during period II leads to increasing pricing trends along the booking horizon (Table 1); the opposite situation draws to a pricing contention and an irregular variability across the booking horizon; and similar elasticities during the two periods results in flat and slightly increasing pricing trends and differences in elasticities in both periods. Regarding the bookings, they depend on the levels of prices estimated in the models. However, time variable also influences the booking levels, this is the natural demand variability along the booking horizon that is not directly related to the price elasticity of demand, for example the reservation peaks that take place after the Christmas and Easter holidays and at the beginning of summer.

3.6 Conclusions

The first objective of this study was to apply and adapt two extended models used in the literature to estimate optimal prices in the transient demand segment for two Majorcan resort hotels. The seasonality and variability of prices present in the sector,

in combination with the lack of development of specific models and their empirical testing in the resort hotel specific context, places the subject in an interesting field of study. In this specific case, OP allows for the hotel to maximize seasonal revenue with limited capacity and for the definition and estimation of different online demand functions, where the own-price elasticities and the effect of the time along the booking horizon are considered. The first type of models, the deterministic models, consists of setting the prices that allow for revenue maximization along the booking horizon; this model reflects different customer behaviors depending on the reservation time (Talluri and van Ryzin, 2004b). The second type, the stochastic models, captures the random fluctuations of demand and allows them to differ from average demand (Badinelli, 2000; Guadix et al., 2010; Talluri & van Ryzin, 2004b).

The comparison of the models' outcomes for two Majorcan hotels show that both models meet the objective of defining the optimal price for obtaining maximum hotel revenue for each date of stay. However, deterministic models usually provide higher levels and more variability in pricing, while they present lower level of reservation variability across the booking horizon. In accordance with the evidence provided by the literature, when the two model estimations are compared with the observed prices, we observe that the price estimations obtained from the stochastic model are more similar to the observed prices from the last season (year 2016). Meanwhile, the average prices from the last three seasons (years 2014-16) are more similar with the estimations obtained from the deterministic model. In that case, deterministic dynamic models usually produce more optimistic forecasts in terms of hotel revenue estimations, like in Guadix et al. (2010).

The second objective of the paper was to compare the outcomes of both models and their estimations. The results obtained indicate the following:

- (1) At the hotel level, the increase in the number of rooms available within the models' forecasts leads to lower levels of prices (Perakis & Sood, 2004; Pan, 2007);
- (2) The elasticity values and capacity cannot explain most of the price differences between the two hotels. Despite this, the specific booking characteristics, tourist profile, seasonality effect, and the hotel location have an important explanatory power as sources of differential pricing among hotel establishments;
- (3) When the booking horizon is limited, the elastic demand estimates lower levels of revenue compared with the inelastic demand;
- (4) The reservations trends along the booking horizon depend on the levels of prices estimated in the models, the distribution of the elasticities, and the impact of the natural variability of demand.

Further research will focus on empirical models testing other types of hotels—different star rating, hotel segments, demand composition, etc.—as well as other hotels in different destinations in order to better compare diverse optimal seasonal prices and revenue levels. The models can also be tested with new data as the booking horizon

goes on (current data); these partial estimations can have some impact on the OP and revenue estimations by transforming the outcomes with more dynamic processes

Some limitations of the study are that the availability of competitors' information, the consideration of additional booking information, such as the number of guests, room type, board, cancellation policies, loyalty programs, etc., as well as other segment data, such as tour operator demand, could improve model estimations.

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Chapter 4. Sources of Price Elasticity of Demand Variability Among Spanish Resort Hotels: A Managerial Insight

Abstract

One of the best methods for segmenting the hotel demand is to determine and compare the different consumer behaviors through the estimation of demand functions. In the present paper we study the sources of price elasticity variability in resort hotel of several Spanish destinations. In order to achieve this goal, we estimate online demand functions during high season for seven 4-star resort hotels located in different Spanish destinations and we compare the different own-price elasticity of demand values. The results indicate that: (1) most of the high season periods present elastic demands, but hotel factors such as the location in the heartland of the resort, a recent hotel renovation, the supply of additional facilities and services, the belonging to the couple and/or half board customer segments, and a higher proportion of German tourists turns the demand more inelastic; (2) the hotels located in Tenerife present the most price-elastic demand during high season; (3) during the closest booking periods to the date of stay demand is usually more elastic; and (4) the number of local competitors push down hotel price levels.

Key words

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

4.1. Introduction

Tourism products involve a whole range of heterogeneous activities: hotel services, restaurants, leisure services, transport services, etc. Among tourism businesses, pricing is considered a basic tool in their revenue maximization processes due to its specific characteristics and the relevance of tourist behavior (Cheng et al., 2011). Specific hotel sector characteristics, such as perishability, capacity limitations, and demand volatility (i.e., seasonality), make demand and occupancy management the basic tools for revenue determination (Anderson and Xie, 2010). Through price variations, a revenue manager can adjust the demand when the available occupancy differs from the occupancy that maximizes revenues. Thus, the literature defines Revenue Management (RM) 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 (Legohérel et al., 2013; Ivanov and Zhechev, 2012; Ivanov, 2014; Smith et al., 1992). The consideration of demand heterogeneity, as well as its seasonal fluctuations, enables customer segmentation. Segmentation is considered a basic RM tool as it allows customer aggragation according to price sensibility and interrelations between the different segments. The high levels of competitiveness that the literature usually

confers to the hotel sector have led market segmentation to be considered a basic tool for hotel survival and market success (Dolnicar, 2002). In this sense, Talluri and Van Ryzin (2005) analyze the heterogeneity of demand under three perspectives: (1) product diversity, (2) demand diversity, and (3) moment/time. Among the various different RM strategies, pricing is considered to be flexible and easily adjustable in the hotel sector's dynamic and competitive environment (Hung et al., 2010).

Several factors enable demand segmentation, which can cause price variability within the same hotel and/or between hotels. Firstly, hotel internal segmentation is directly controlled and managed by hotel managers and affects issues such as booking date, rate fences, type of tourists, and seasonality; and secondly hotel external segmentation, which is not directly controlled by the RM department, at least in the short-run, and includes issues such as hotel attributes, customers' perception of these attributes, and destination context (Vives et al., 2018-a). One of the best ways to measure these issues is to determine consumer behavior and their willingness to pay through the estimation of demand functions. Finally, RM literature places optimal dynamic pricing as the most extended model used in hotel revenue maximization, where room prices are set to maximize revenue over the booking horizon (Bandinelli, 2000).

The aim of the paper is to find which are the sources of price variability in resort hotels of different Spanish destinations. In order to achieve this goal, the study presents an implementation of demand functions and modeling used to estimate own-price elasticity of demand (Vives et al., 2018-b and Vives and Jacob, 2018) for different resort hotels located in several Spanish destinations. Hence, firstly, we estimate and compare different elasticity values from the online transient demand of different tourist destinations, seasons, and booking horizons; and secondly, we explore hotel location, specific hotel attributes, and customer characteristics that can explain the differences in elasticities between hotels and different Spanish destinations. The value added of the study is that the pricing differences among different reservation dates, seasons and hotels are explained on the basis of customer behavior, while their managerial implications are also investigated. The prevailing literature on the topic focuses on hedonic pricing models, which examines price heterogeneity among hotels, but these models do not allow for the identification of consumers' willingness to pay (Aguiló et al., 2001).

The empirical application was carried out with data from several resort hotels belonging to a multinational hotel chain in three Spanish tourism destinations: The Balearic Islands, the Canary Islands, and Andalusia. In 2017 Spain received over 100 million tourists who chose hotel establishments for lodging, which resulted in more than 340 million overnight stays (INE, 2018). The main Spanish regions in terms of hotel overnights, specialized in the 'sun and beach' segment, are Andalusia, the Balearic Islands, and the Canary Islands, and these three regions generated more than 183 million overnight stays during 2017 (almost 55% of the total). In the same way, the multinational hotel chain selected for this study has all its Spanish resort hotels located in these three regions. The category of all the hotels included in our study was four stars.

The structure of this paper is organized as follows. After the introduction, section 2 presents a literature review focused on hotel RM and price elasticity of demand. Section 3 describes the methodology, presenting the demand function model for the resort hotel sector. Section 4 details the data, starting with an overview of the context of hotels' destinations (section 4.1) and then goes on to describe hotel specific characteristics (section 4.2). Section 5 outlines the main results and discusses the implications of elasticity estimations; finally, in section 6, we present the main conclusions and the implications for the design of hotels price and revenue management strategy.

4.2 Literature review

As the literature points out RM is defined 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 (Legoh  rel et al., 2013; Ivanov and Zhechev, 2012; Ivanov, 2014; Smith et al., 1992). In this sense, the sector's characteristics (perishability, capacity limitations, and seasonality) confer considerable power to the management of demand and occupancy over the booking horizon in order to determine hotel revenue (Anderson and Xie, 2010). The essence of RM is understanding the perception of customer segments concerning hotel products and aligning them with product prices and availability (Cross et al., 2011).

Customer segmentation is a basic tool in RM; segmentation considers the heterogeneity of demand and its seasonal fluctuation, as well as the interrelations between segments. Therefore, 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 where customers share similar responses to price and marketing variations, i.e., the way they purchase, their product valuation, and their willingness to pay (Talluri and Van Ryzin, 2005), which will help to enhance customer satisfaction (Zhang and Bell, 2012). In the hotel sector, segmentation not only represents the tactic of varying prices across customers, situations, and over time (Wu et al., 2012), it is also influenced by the destination's characteristics, past marketing measures, and external factors (Rondan-Catalu  a and Rosa-Diaz, 2014). However, segmentation in the hotel industry, as well as its influence on pricing, is very diverse and depends on several factors, and can be classified as internal and external segmentation (as in Vives et al., 2018-a).

Internal segmentation is directly controlled and managed by the RM department; in fact, revenue managers consider several factors that enable the control of hotel revenue in the short-run; these factors can be considered sources of hotel price variability. Thus, Kim et al. (2016) state that internal segmentation and RM pricing decisions are affected by economic market conditions, events, seasonality, and booking time. Vives et al. (2018-a) classify the internal sources of price variability which allow internal hotel segmentation, these are the following:

1. Booking dates: Hotels usually limit the number of rooms sold at some points of the booking horizon in order to keep them for more profitable customers that book later (Aziz et al., 2011), this fact is due to limited hotel capacity (Bandinelli, 2000). Therefore, different market segments are able to exhibit different reservation patterns over the booking horizon (Bandinelli, 2000; Lee, 2011).
2. Rate fences: The rules that allow demand segmentation and explain differential pricing are called rate fences (Liu et al., 2014), which usually include consumption characteristics (refundability on advance reservations, minimum length of stay, group size), product characteristics (room location, room type, board), customer membership to some groups, customer loyalty, and early booking offers (Ivanov, 2014).
3. Tourist types: Each tourist segment presents different price sensitivities (Desiraju and Shugan, 1999), thus, it is important to understand, segment, and align the hotel product with tourist perceptions of product value (Cross et al., 2011).
4. Seasonality: Coenders et al. (2003) find that during the peak season prices can double or more than double in the hotel resort sector. Thus, demand fluctuations have a significant impact on peak and low-season optimal hotel prices (Gallego and Van Ryzin, 1994; Pan, 2007). Collins and Parsa (2006) point out that the highest prices are offered during peak demand periods, while discounts are carried out during low-demand periods in order to boost demand.

Meanwhile, external segmentation is used to segment customers and is not directly controlled by the RM department (Vives et al., 2018-a). External segmentation is sometimes related to the diversity of hotel attributes and categories, as well as to the way customers perceive these attributes. In the short and medium-run these hotel characteristics cannot be changed, i.e., they represent hotel differential pricing. Vives et al. (2018-a) classifies the sources of price variability related to hotel differentiation, the external hotel segmentation, in:

1. Price effect of hotel attributes: the hedonic price theory is one method used in the literature to measure the value of hotel attributes which are not sold individually (Espinete et al., 2003). The hotel star category is the most common attribute affecting the price (Abrate and Viglia, 2016; Aguiló et al., 2001; Balaguer and Pernías, 2013; De la Peña et al., 2016; Espinete et al., 2003; Ivanov and Piddubna, 2016; Juaneda et al., 2011; Soler and Gémar, 2016; Thrane, 2005; Yang et al., 2016), as well as the hotel online rating (Abrate and Viglia, 2016; Ivanov and Piddubna, 2016; Soler and Gémar, 2016; Yang et al., 2016). A second popular factor in the literature is hotel establishment location, or distance to the beach or city center (Abrate et al., 2011; Aguiló et al., 2003; Balaguer and Pernías, 2013; Coenders et al., 2003; Espinete et al., 2003; Juaneda et al., 2011; Lee and Jang, 2011; Papatheodorou, 2002; Soler and Gémar, 2016;). White and Mulligan (2002) find that hotel-chain affiliation explains much of the price variation, while Balaguer and Pernías (2013) estimate strong positive coefficients for two hotel chains. Finally, other attributes affecting prices are type of board (Aguiló et al., 2001; Aguiló et al., 2003; Thrane, 2005),

availability of parking (Coenders et al., 2003; Espinet et al., 2003; Lee and Jang, 2011; Thrane, 2007), hotel and room characteristics (Coenders et al., 2003; Espinet et al., 2003; Monty and Skidmore, 2003; Papatheodorou, 2002; Thrane, 2005; Thrane, 2007; White and Mulligan, 2002), and hotel surroundings such as temperature, urban location, and economic features of the region (White and Mulligan, 2002).

2. Customer perceptions of hotel attributes: another form of external segmentation is to understand the appraisal of hotel attributes by different customer segments, since they directly affect tourist behavior and satisfaction (Kang et al., 2004). Tsaour and Tzeng (1996) point out that reputation, image, and good transport links represent the most important attributes in the hotel selection decision process. Danziger et al. (2006) find that the most important sources of information are star ratings and price, while brand information can replace the star rating when it is not available. Shieh et al. (2014) place hotel size and age, as well as proximity to the nearest international airport, as the most attractive attributes for consumers. Similarly, Noone and McGuire (2013) find that consumer reviews are one of the key determinants in the purchasing process of hotel rooms.
3. Hotel destination heterogeneity factors: it must be emphasized that destination heterogeneity affects external segmentation. On the one hand, hotel heterogeneity is determined by the agglomeration factor, as it can assist the reduction of consumer search costs (Canina et al., 2005), as well as the generation of positive externalities that may induce location near competitors (Urtasun and Gutiérrez, 2006). On the other hand, the differentiation factor has to be considered; for instance, Canina et al. (2005) find that higher levels of differentiation have a negative impact on the low-cost segment and a positive impact on the luxury and high-price hotel segments, as the latter increases the attractiveness of the area.

In summary, there are several sources of price variability that influence hotel customer segmentation and the resulting influence on pricing. However, knowledge of consumer behavior and the possibility of measuring their willingness to pay (price elasticity of demand) provide a good way to segment the demand and charge them the correct price. Therefore, demand function determination enables the measurement of demand changes under different market conditions and price levels, i.e. customer willingness to pay, as well as representing a powerful method for hotel revenue maximization (Lee, 2011; Lee et al., 2011). Once the hotel is able to differentiate market segments, it can set different prices for each segment, i.e. price discrimination, as each segment is made up of individual consumers with homogeneous demand patterns and price response (Ng, 2009). In fact, the sector is dealing with different interrelated segments, and it has the particular feature that a room that is sold to one type of guest at a specific time cannot be sold in the future due to the hotels' capacity constraints. The presence of demand modeling in the hotel RM literature is quite widespread; for instance, Hormby et al. (2010) use demand modeling in order to segment hotel demand, the main hypothesis being that customer responses change depending on the occasion, group size, and season. Lee (2011) uses variables such as price, reservation date, length of stay, and the day of arrival within the week in order

to measure demand differences between airport, suburban, and urban hotel segments, finding that hotel demand in general is demand-inelastic and that the same hotel typology located in similar tourism locations exhibits similar demand patterns. Aziz et al. (2011) use a probit function to estimate demand, and they find that hotel demand is quite elastic and constant during the period considered. Perakis and Sood (2004) highlight the fact that prices increase when lower price sensitivities take place, but decrease when the number of available rooms increases. Rondan-Cataluña and Rosa-Diaz (2014) group hotel clients in two segments: an elastic segment and an inelastic segment. The elastic segment considers hotel prices to be fair and are willing to pay 6% more for a room. Meanwhile, the inelastic segment is not willing to pay more for a hotel room, despite showing higher levels of loyalty. Guo et al. (2013) use linear and non-linear demand functions in order to estimate the optimal number of demand segments to be differentiated along the booking horizon which allow the revenue maximization.

4.3 Methodology

Online transient demand (Q_d), which is represented by online room bookings, for a specific date of stay (d) can be defined as a function of the price set by the hotel revenue manager (p_d) and the reservation time over the booking horizon (r_d). Thus, the demand function can be expressed as follows:

$$Q_t^d = f(p_t^d, r_t^d) \quad (1)$$

Where time: $t = 1, 2, \dots, d$.

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

Price elasticity of demand can be estimated, which enables the demand to be quantified when the price changes (Chatwin, 2000; Ivanov, 2014; Shy, 2008):

$$\varepsilon = \frac{p}{Q} \frac{\Delta Q}{\Delta p} \quad (2)$$

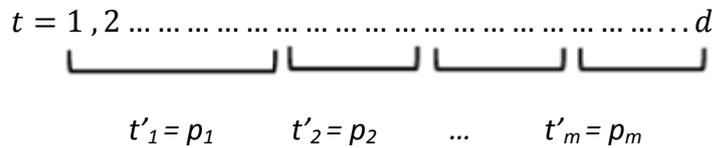
Elasticity values allow the comparability of the different demand reactions to price variations over different booking times, different dates of stay, and different hotel establishments.

The specific hotel demand function used will provide us with the elasticity values and the booking time effects on hotel online transient demand. It is a linearized Cobb-Douglas demand model used by Vives et al. (2018-b) and Vives and Jacob (2018), where daily room bookings (Q) are transformed into the average number of daily room reservations (q) for each period of time when p are not changed by the RM department over the booking horizon.

$$\ln q_{t'}^d = \alpha_0 + Dummies_{y,d,b} + \beta_p \cdot \ln p_{t'}^d + \beta_r \cdot \ln r_{t'}^d \quad (3)$$

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

In this case, t' represents a variable period of time where p remains constant (as in Vives et al., 2018-b).



Dummy variables and factors are grouped as: y the year/season when the observation takes place; d date of stay; b booking period, reservation dates are usually grouped by month or half month – and the dates closer to the date of stay frequently require more observations due to increased booking activity.

The use of this demand function enables the elasticity values to be directly measured through the e value (Pachon et al. 2006).

To sum up, the demand function defined considers the effects of price, booking horizon, and date of stay on the online transient demand of hotel rooms.

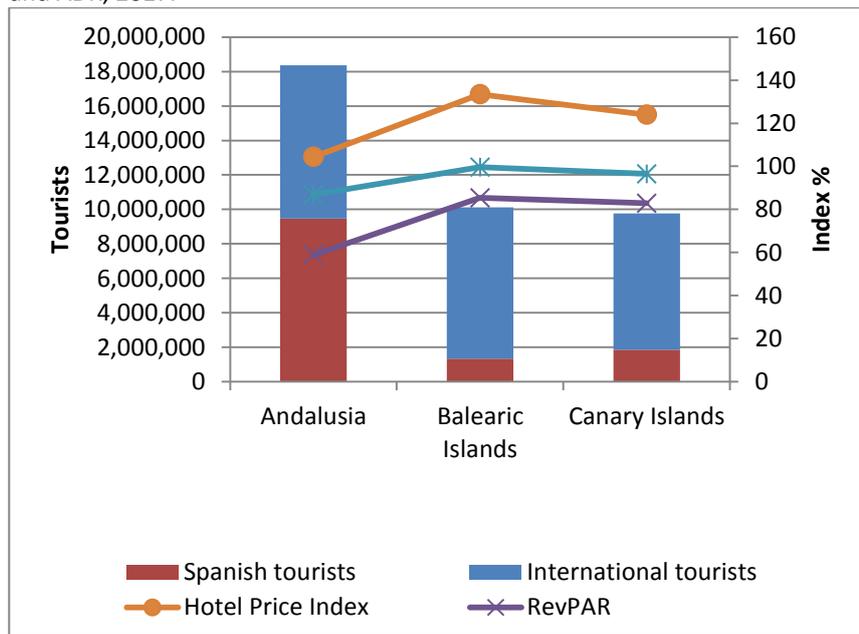
4.4 Data

The study uses data on prices and bookings from seven 4-star hotels belonging to the same multinational hotel chain, two of which are located in Majorca (Balearic Islands), two in Tenerife (Canary Islands), and the last three are located in Málaga, Cádiz, and Huelva (Andalusia). The RM department of the hotel chain provided the data for the study.

4.4.1 Regions context

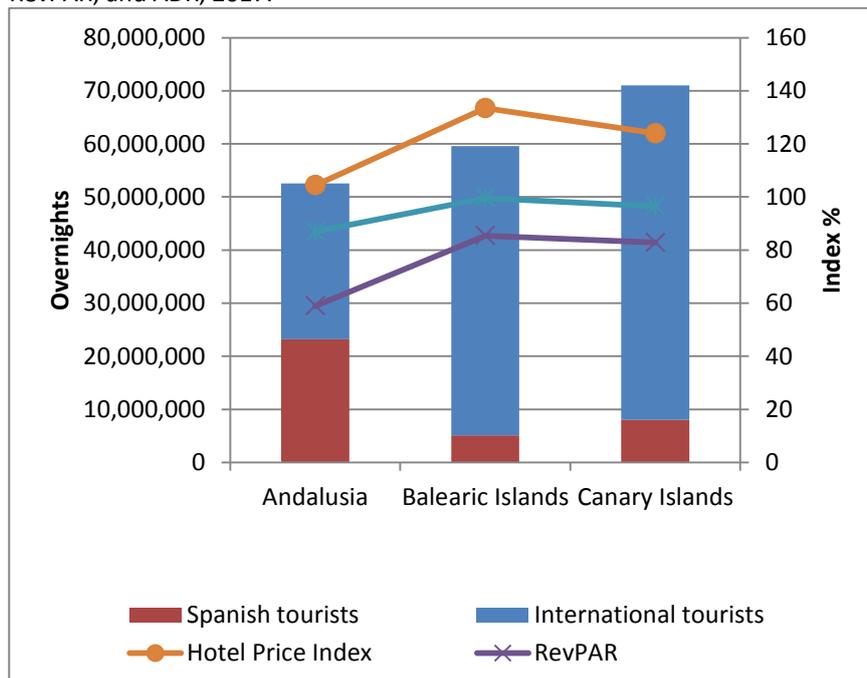
The destination context is able to explain part of the hotel prices and demand differences that the present paper proposes. In terms of number of tourists (*Figure 1*) Andalusia gathered almost 18 million visitors staying in hotels in 2017, 52% were domestic tourists; while the Balearic Islands received more than 10 million tourists who stayed in hotels, 87% were international tourists; and the Canary Islands accommodated almost 10 million tourists in hotels, 81% were international tourists (INE, 2017). Furthermore, Andalusia had the lowest hotel prices, specifically 21.8% lower compared to prices in the Balearic Islands; in fact the Balearics had the highest prices, while the Canaries had prices just 7.2% lower than the other archipelago. The Revenue per Available Room index (RevPAR) also took the highest value in the Balearic Islands, 3% greater than the value reached in the Canary Islands, and 31% higher than in Andalusia. Finally, the Average Daily Rate (ADR) was higher in the Balearics, 3.1% higher than in the Canaries, and 12.8% greater than in Andalusia.

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



Source: INE (2018).

Figure 2. Regional breakdown of number of overnight stays in hotels, Hotel Price Index, RevPAR, and ADR, 2017.



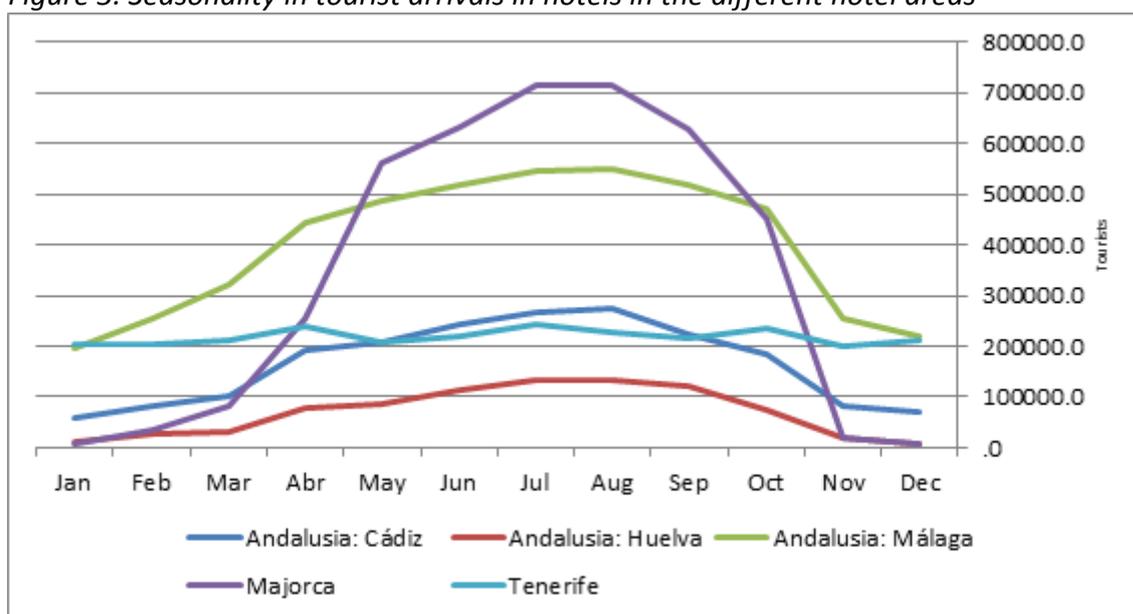
Source: INE (2018).

However, when considering hotel overnight stays in 2017 (*Figure 2*), the Canary Islands had the highest value; specifically, 89% of the total 70 million overnight stays corresponded to international tourists. The Balearic Islands generated almost 60 million overnight stays, 91% by international tourists. Finally, in Andalusia there were 52.5 million overnight stays, 55.8% of which corresponded to international tourists.

In terms of number of visitors (*Figure 3*), the Majorca area,⁸ where two of the hotels of the study are located, showed the largest seasonality; 65% of the 4.1 million tourists staying in hotels arrived in summer (June-September). One of the three hotels in Andalusia is located in Málaga (specifically in the Costa del Sol area), it is a province that gathered 4.8 million tourists and displayed the second highest seasonality, 60% of tourists arrived during the summer months. Another hotel is located in Cádiz (more specifically in the Costa de la Luz area) where half of the 2 million tourists that it receives arrived during the summer months. Huelva (Costa de la Luz area) is the last province in Andalusia where one hotel is located, 45% of the 0.8 million tourists that it receives arrived between June and September. Finally, Tenerife gathers two hotels located in the South part of the island; it showed a constant affluence of tourists all year round, a third of the 2.6 million tourists arrived during summertime.

In 2017 the number of tourists increased in all areas due to the growth of international tourism; specifically, in the Majorca area the number of tourists rose by 2.1% compared to the previous year. The average growth in the three Andalusian areas was also 2.1%, and it was 0.4% in Tenerife.

Figure 3. Seasonality in tourist arrivals in hotels in the different hotel areas

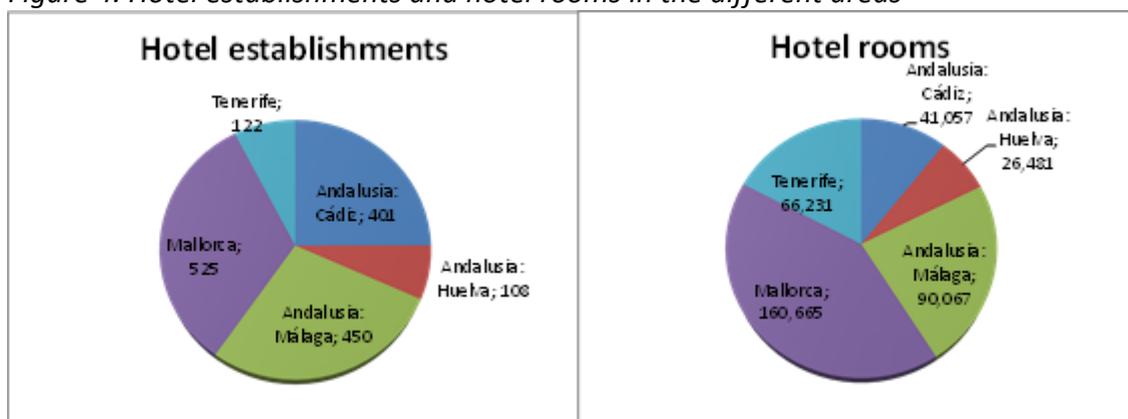


Source: INE (2018)

In terms of the level of potential regional competitors (*Figure 4*), the number of hotels in the Majorca area is 525 establishments, which amount to almost 160,000 hotel beds. The Málaga area contains 450 hotels, but only represents 90,000 beds. Cádiz has 400 hotels and over 40,000 hotel beds. Huelva holds more than 100 hotels and 25,000 hotel beds. Tenerife has 122 hotel establishments and 66,000 beds. Finally, the hotel occupancy rates of the available rooms was 86% in Tenerife, 84% in Majorca, 77% in Málaga, and less than 65% in Cádiz and Huelva; while the average stay was 7.6 days in Tenerife, 6.5 days in Majorca, and less than 4.5 days in the Andalusia areas.

⁸ The area is the whole island of Majorca except for the Palma area and Calvia.

Figure 4. Hotel establishments and hotel rooms in the different areas



Source: INE (2018)

4.4.2 Hotel features

The present study uses data from seven 4-star hotels – i.e., with an identical star rating, hence, we avoid one of the most important sources of differential pricing (Abrate and Viglia, 2016; Aguiló et al., 2001; Balaguer and Pernías, 2013; De la Peña et al., 2016; Espinet et al., 2003; Ivanov and Piddubna, 2016; Juaneda et al., 2011; Papatheodorou, 2002; Soler and Gémar, 2016; Yang et al., 2016). Two are located in Majorca, two in Tenerife, and the last three are located in Málaga, Cádiz, and Huelva (the last three belong to Andalusia, the largest Spanish region); all the hotels belong to the same multinational hotel chain, one of the top five multinational hotel chains in Spain. Regarding hotel chain information, it annually sets individual hotel prices that vary according to the seasonal period of stay, type of room, type of board, guest type, booking date, length of stay, and method of payment.

Seasonality is considered an important source of price variation (Abrate et al., 2011; Monty and Skidmore, 2003; Yang et al., 2016). The highest prices were found during July and August in all hotels except in the Tenerife establishments, because in the Canary Islands the summer months represent the low season. For example, in the Majorca hotels the peak season prices were 100-115% higher than the low season ones, and accounted for 31-39% of yearly reservations; in the hotel in Cádiz the peak season prices were 110% higher and 31% of yearly reservations were made during the high season (opens in winter time); in the hotel in Huelva the prices were 120% higher in the peak season when 41% of reservations took place; in the hotel in Málaga prices increased around 75% during the peak season when 43% of reservations took place; finally, prices in the hotels in Tenerife increased by 60-45% during the peak season December-January, when the low season is in April-June and 20% of reservations took place, but the price difference between May-June and July-August was 20-25%.

When we analyzed the price evolution over the booking horizon, we observed that during the first stages of reservations each hotel sets three predetermined early booking periods offering discounts between 5% and 15% depending on the time. Then, during the entire booking horizon the revenue manager was able to alter prices

throughout according to date of stay, sales rate, and occupancy levels (Abrate and Viglia, 2016; Ivanov and Piddubna, 2016; Juaneda et al., 2011; Soler and G mar, 2016).

Table 1 describes the characteristics and attributes of all the hotels included in the study, which the literature has proved to affect hotel prices. For instance, all the hotels are located on the coast line with nearby beaches – one of the most important factors that influence prices (Coenders et al., 2003; Espinet et al., 2003; Papatheodorou, 2002; Thrane, 2005) – and supply services such as local, national, and international food, show cooking, Wi-Fi, fitness and several sport facilities (Aguil  et al., 2001; Aguil  et al., 2003; Thrane, 2005). Most of the hotels are located in the resort heartland, while just the Huelva’s hotel is located in a remote natural area. Hotel size ranges from 300 to over 600 rooms and the literature indicates that size is a source of price differentiation (De la Pe a et al., 2016; Balaguer and Pern as, 2013; Hung et al., 2010; Ivanov and Piddubna, 2016; Shieh et al., 2014; Soler and G mar, 2016; Thrane, 2005; White and Milligan, 2002). Market segment is considered another source of price variability (Aguil  et al., 2001), in this case half of the hotels focus on the family market, while the other half focus on the couples market, but all of them accept children. Type of board can lead to differences in prices (Aguil  et al., 2001; Juaneda et al., 2011; Papatheodorou, 2002), three hotels are specialized in all-inclusive bookings, while the rest combine half board and all-inclusive bookings. The Majorca hotels focus more on the German and UK markets, Tenerife on the UK market, and Andalusia on the German and national markets; in fact, tourist nationality is considered another source of price influence (Aguil  et al., 2003). The longest lengths of stays usually take place on the islands (Majorca and Tenerife), on average one day longer compared to the Andalusian hotels. In general, all the hotels obtain high online rating scores, but the largest hotels located in Majorca and Tenerife have the lowest rates, as hotel size is a source of differential pricing (Abrate and Viglia, 2016; Ivanov and Piddubna, 2016; Soler and G mar, 2016; Yang et al., 2016). Finally, the supply of hotel facilities and services also affect the level of prices (Abrate and Viglia, 2016; Aguil  et al., 2001; Aguil  et al., 2003; Espinet et al., 2003; Ivanov and Piddubna, 2016; Juaneda et al., 2011; Lee and Jang, 2011; Thrane, 2007; Yang et al., 2016; White and Milligan, 2002), in this case the Andalusian hotels show a larger range of specific facilities and services, while the Tenerife hotels have a lower supply of facilities and services.

Table 1. Hotel characteristics.

Hotel		Hotel 1		Hotel 2		Hotel 3		Hotel 4		Hotel 5		Hotel 6	
Location		Resort heartland		Resort fringe		Resort heartland		Resort heartland		Resort heartland		Resort fringe	
		Alcudia		Santanyi		Adeje		Adeje		Chiclana		Torrox costa	
		Mallorca		Mallorca		Tenerife		Tenerife		Cádiz		Málaga	
Star rating		4		4		4		4		4		4	
Room number		360		619		404		505		413		413	
Booking Characteristics	Type of tourist	Couples	Families	Couples	Families	Couples	Families	Couples	Families	Couples	Families	Couples	Families
		60%	27%	13%	73%	46%	38%	65%	22%	45%	39%	40%	51%
			Kids		Kids		Kids		Kids		Kids		Kids
		16%		31%		16%		7%		20%		19%	
	Board	HB	AI	AI		AI		HB	AI	HB	AI	HB	AI
		50%	17%	100%		96%		53%	30%	42%	43%	48%	44%
Tourists nationality		Germany	UK	UK	Germany	UK	Benelux	UK	Spain	Spain	Germany	Germany	Spain
		32%	19%	26%	24%	49%	13%	47%	12%	44%	29%	29%	26%
Online Bookings		32%		32%		31%		24%		37%		35%	
Length of Stay	1-3	6%		15%		6%		12%		18%		15%	
	4-8	59%		51%		64%		53%		56%		55%	
	(+)8	0.35		34%		30%		35%		26%		30%	
	Average (days)	7.93		7.45		7.57		7.61		6.82		7.18	
Online ratings	Hotel chain webpage	8.8		7.5		8.8		7.5		8.8		8.8	
	Booking	8.5		8.4		8.7		8.6		9.3		8.5	
	Tripadv	4.5		4		4.5		4		4.5		4.5	
Hotel Facilities & Services	Family hotel			X		X						X	
	Renewed	X						X		X		X	
	Spa	X		X						X		X	
	Music & Shows	X		X						X		X	
	Golf									X			
	Gourmet restaurant									X			
	Beauty & Relax					X						X	
	Natural area location												

Source: Own Elaboration.

4.5 Results and Discussion

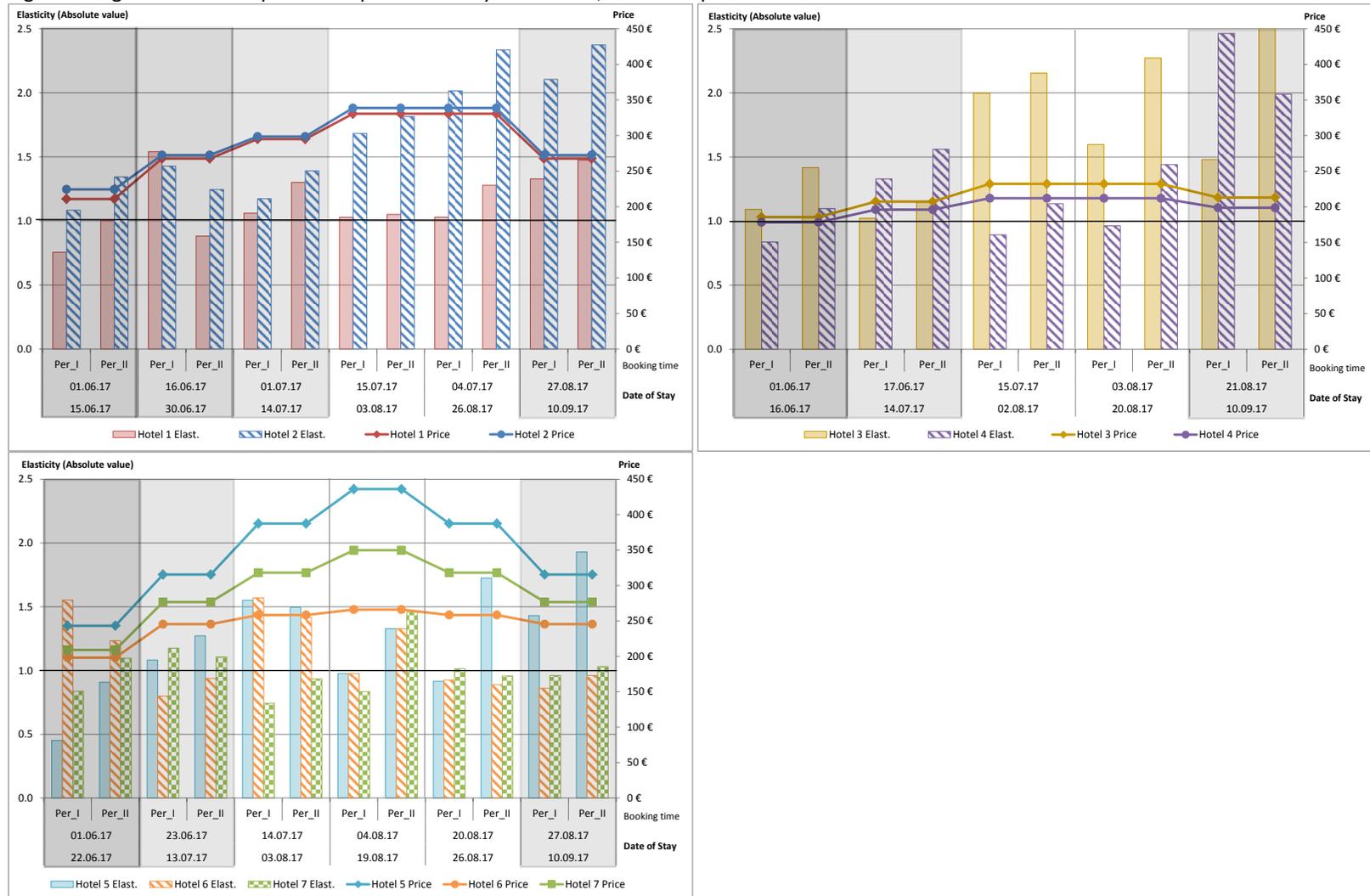
As mentioned in the introduction, the aim of the present article was to study the sources of price variability in resort hotels of different Spanish destinations. For that purpose we have studied the demand at the level of hotel establishment and how it changes over time⁹; however, the demand function used cannot isolate hotel attributes or location or some demand segment characteristics in the demand function. So, although we compared and analyzed the differences in elasticity values, these differences may be partly caused by hotel attribute demand valuations or different demand characteristics, which are not directly measured by these demand functions. Nevertheless, we contrast and check the general weight of these attributes and demand characteristics in the elasticity values in several multiple-hotel regressions that can be found in the annex section. Overall, the Andalusia's hotels are the most inelastic one, the Tenerife's hotels are slightly more elastic compared with hotel 1 in Majorca, and *hotel 2* is the most elastic of all hotels studied (*Table 2*, annex). Meanwhile, hotel or demand characteristics such as larger hotel size, family and all-inclusive board segments specialization, and the larger length of stay lead to more elastic online demands; and the hotel online rating, the hotel renewal or to own a Spa tend to make the demand more inelastic (*Table 3*, annex).

More specifically, *Figure 5* shows the different prices and elasticity values that the seven hotels exhibit throughout the high season. In general terms, the recommendation for managers is to increase prices and contain occupancies when the demand is inelastic, and to reduce prices and increase occupancies when it is elastic, however, the capacity limitations and the demands elasticity distributions across the booking horizon are able to break these rules (Vives et al., 2018b; Vives and Jacob, 2018).

Regarding hotel prices, in general, the highest level of prices in the high season involves a larger seasonal variability of price; indeed, Gallego and Van Ryzin (1994) and Pan (2007) highlight the fact that hotel seasonal prices are directly influenced by demand fluctuations. Therefore, the two hotels in Tenerife show the lowest price levels in July-August –as opposed to the hotels in Andalusia with the lowest average price levels (*Figure 1* and *2*) – and the lowest price variability across the different seasons considered in the study –as it is the destination with a constant affluence of tourists throughout the year – while the hotels located in Majorca and Cádiz exhibit the highest results (*Figure 5*). Concerning elasticity values (*Figure 5*), most of the periods reveal elastic demands (as in Aziz et al., 2013). However, higher price levels usually involve more inelastic demands, i.e., the peak season periods, as well as hotels with specific attributes, such as recently renewed hotels, a larger supply of additional facilities and services, specialization in couple and/or half board segments, shorter lengths of stay, and a greater proportion of international tourists, particularly the German market, which is especially relevant in the case of *hotel 1* in Majorca and *hotel 6* in Cádiz. Meanwhile, lower price levels, larger hotel size, specialization in all-inclusive

⁹ In practical terms, the revenue manager changes all the hotel prices as a unitary price over the booking time and the dates of stay, although different types of rooms have different prices.

Figure 5. 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.

and family segments, and specialization in UK and national market are factors that lead to more elastic demands (for instance, *hotel 2* in Majorca or *hotel 3* in Tenerife).

The two hotels located in Majorca have moderate elastic demand levels during June and the first half of July, the periods prior to the peak season, and then for *hotel 1* the elasticity becomes unitary (around -1), while for *hotel 2* the demand progressively becomes more elastic across the peak season. In general, the most elastic demands are found just after the peak season. These seasonal divergences between both hotels can be partially explained by differential pricing and differences in online demand. Nevertheless, in general, of the two Majorca hotels, *hotel 2* exhibits the highest elasticity, this hotel shows most of the factors that usually lead to elastic demands, such as the fringe location in the resort area, a larger hotel size, lower online rates, a focus on the family and all-inclusive segments, and a focus on the UK market; while *hotel 1* is located in the resort heartland area, focuses more on the couple and half board segments, was recently renewed, and one third of the tourists come from Germany. Rosselló et al. (2005) obtained similar results, i.e., the British market is more elastic than the German market in Majorca.

The hotels in Tenerife on average take the highest elasticities of the study, they also exhibit an increasing elasticity trend across the high season, generally fluctuating between -1 and -2 –which points out that these hotels should reduce prices if they want to improve occupancies and so their revenue. It has to be considered that during the Spanish high season the Tenerife hotels have the lowest prices of all the hotels, because the summer months are considered the medium season in the island, as the high season in Tenerife takes place in winter. It is also worth highlighting that Tenerife is located far away from the main country of origin of tourists, and Yang et al. (2016) find that higher cost of reaching the destination leads to lower hotel prices. During the peak season periods the demand for *hotel 3* is significantly elastic, which is when the rest of Spanish destinations receive the greatest numbers of tourist arrivals and competitiveness in the resort hotel segment is at its highest level, while *hotel 4* presents more moderated elasticity values. None of the hotels had been recently renewed, a factor that increases their elasticity levels, while both are located in the same part of the resort area. In general, *hotel 4* exhibits the most inelastic demand: although the hotel is more focused on the family segment (usually the most elastic), it is a smaller hotel with 100 rooms fewer than *hotel 3*, it is focused on the half board segment (almost all the demand of *hotel 3* books all-inclusive board), has higher online rates, and a lower proportion of UK and Spanish tourists, all of which are factors that reduce elasticity levels.

The hotels located in Andalusia exhibit a great range of elasticities, but they present the most inelastic demands during almost half of the seasonal periods. More specifically, *hotel 5* (Cádiz) exhibits inelastic demands in August and at the beginning of June. For the Málaga hotel (*hotel 6*) – the area with the highest number of tourist arrivals in Andalusia – in June and the first half of July the demand is usually more elastic, while from the peak season on it becomes inelastic. Finally, in Huelva (*hotel 7*) more inelastic demands are exhibited in peak season. In general, the hotels in

Andalusia have the highest online rates, had all been recently renewed, provide a wider range of additional hotel facilities and services, and have the shortest length of stay; and these factors reduce elasticity levels. The proportion of tourists is distributed fairly between the national and German markets, with opposing effects on elasticities. More specifically, *hotel 5* shows the highest prices, but it should be emphasized that it is the only hotel to have a golf course among its facilities and it is located in the resort heartland area, which is a factor that can help to attract the most inelastic demand segments. Furthermore, this is the Andalusia's hotel that focuses more on the couples segment, and has the highest online rates. *Hotel 6* focuses on the family segment – elastic factor–, while exhibits the longest length of stay among the Andalusia hotels, it is located in the resort fringe area, focuses more on the international market and presents beauty and relax facilities –inelastic factors. While *hotel 7* also focuses on the family segment, half of the tourists are national, and it is located in a remote area with the least affluence of tourists; however, it presents beauty and relax facilities, and it is located in a natural area.

When we analyzed booking horizon elasticities, except for the hotel in Málaga, Period I (the farthest from the date of stay) tended to have the most inelastic demands. This result could be explained by the fact that tourists booking in Period I are willing to book a hotel at that specific date and location, while tourists booking in closer periods to the date of stay may relax these requirements. Theoretically, the typical effect reflected in RM literature is that the lowest prices are found during the early booking stages and then increase over the booking horizon (Aziz et al., 2011; Desiraju and Shugan, 1999). However, 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, Melis and Piga (2017) find that resort hotels tend to reduce prices during the last 25 days before the date of stay. Abrate et al. (2012) highlight the fact that price evolution and customer sensitivity variability over the booking horizon also depend on their level of patience.

Competitive effects may also influence hotel differential pricing, especially between the different regions. According to the findings of Abrate and Viglia (2016) the number of local competitors is able to push prices down, which could explain in part the higher prices of some hotels in Andalusia, such as Huelva and Cádiz (*Hotels 5 and 7*), compared to hotels in Majorca and Málaga (*hotel 1, 2 and 6*). Meanwhile, Pachon (2007) indicates that the hotel's levels of substitutability can be a sign of demand elasticity, therefore close, similar hotels focusing on different segments can display different prices and/or elasticities, which might explain the seasonal differences between hotels located in the same destination (Majorca and Tenerife). In the same way, Kim et al. (2004) point out that level of hotel differentiation, as well as hotel reputation, are determining factors in setting higher prices.

4.6 Conclusions

In a hotel managerial approach, the price variations enable the revenue manager to adjust demand at times when the available occupancy differs from the occupancy that

might maximize hotel revenue, the fact of knowing the sources of price variability will allow better customer segmentation. Thus, customer segmentation represents a basic step in revenue maximization; i.e., the consideration of demand heterogeneity and its seasonal fluctuations enable different customers to be charged different prices for the same product according to their price sensitivity. In this sense, pricing is considered to be flexible and easily adjustable in the hotel sector's dynamic, competitive environment (Hung et al., 2010).

In terms of hotel demand segmentation and sources of price variability, Vives and Jacob (2018) differentiate between hotel internal segmentation – such as booking date, rate fences, type of tourists, and seasonality – which is directly controlled by hotel managers in the short-term; and hotel external segmentation – such as hotel attributes, customers' perception of these attributes, and destination context – which are not directly controlled by hotel managers in the short-term. One of the best methods for measuring these issues is to determine and compare different consumer behaviors and their willingness to pay through the estimation of demand functions.

In the present paper, in order to find the main sources of price variability in resort hotels of different Spanish destinations, we implemented the demand functions used by Vives et al. (2018-b) and estimated different price elasticities of demand. The present study used online transient demand data from seven 4-star hotels belonging to the same multinational hotel chain located in different Spanish regions (two in Majorca, two in Tenerife, and the last three in Andalusia). Although all the resort hotels have similar features, they do have some specific characteristics, such as hotel size, supply of additional facilities and services, tourist market origin, etc., which differentiate each one from the rest, and may explain the different price elasticities. The two-fold way to identify the main sources of price variability was : (1) First, to estimate and compare the different elasticity values across the different resort hotels, seasons, and booking horizons; and (2) second, to explore hotel location, specific hotel attributes, and customers' characteristics that might explain the differences in terms of elasticities, as well as their managerial implications.

Regarding the results of the study, most of the period estimations between June and September (the traditional high season in Spain) exhibited elastic demands. More specifically, factors such as higher price levels, resort heartland area hotel location, recently renewed hotels, larger supply of additional facilities and services, specialization in couple and/or half board segments, shorter lengths of stay, and higher proportion of German tourists involved more inelastic demands. Meanwhile, lower price levels, larger hotel size, specialization in the family segment, and specialization in the national and UK markets were factors that led to more elastic demands.

The hotels located in Tenerife exhibited the most elastic demand over the different high season periods, generally fluctuating between -1 and -2. During the traditional Spanish peak season, the hotels in Tenerife tended to display the most elastic demands, the hotels located in Majorca tended to exhibit more elastic demands during August-September, while in Andalusia the most inelastic periods take place during peak season. In general terms, during the elastic seasons the recommendation is to

reduce prices in order to improve occupancies and hotel revenues, while the inelastic seasons the recommendation is to increase prices in order to contain the occupancies and increase the revenues.

Over the booking horizon, the periods farthest from the date of stay tended to have the most inelastic demands due to perishability; as the date of stay approaches, the possibility of setting a discount increases due to the risk of losing revenue from unsold rooms (Lee, 2016; Melis and Piga, 2017), and the level of patience of tourists (Abrate et al., 2012).

Finally, the number of hotels in the local context is able to explain part of the price differences, i.e., competitiveness; specifically, a larger number of competitors is able to reduce the level of hotel prices (Abrate and Viglia, 2016).

Further research will focus on linking the demand function models with optimal dynamic pricing estimations in the same hotels, comparing the prices set by the hotels-regions with the optimal prices estimated with the demand function outcomes in optimal dynamics pricing methodologies used by Vives and Jacob (2018). Meanwhile, the study's limitations involve the unavailability of competitors' data, which would be able to improve elasticity estimations, as well as additional booking information which could be introduced into the functions, such as the number of guests, room type, board, cancellation policies, etc., as well as tour operator segment data.

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4.8. Annex

As we point out throughout the paper, the weight of hotel attributes demand and different demand characteristics are not directly measured by the demand functions. In order to solve this, we have estimated two general ordinary least squares regressions where the elasticity values across hotels, seasons and booking horizons represent the dependent variable; while the independent variables are the same ones introduced in the demand function and have also included two groups of variables: (1) the hotel dummy variables (h) –take the value 1 when the observation belongs to one of the seven specific hotels, the reference hotel is the number 1–, which allow the estimation of different general effects of the hotels on the different elasticity values; and (2) the hotel attributes and demand characteristics variables.

$$\varepsilon_{t'}^d = \alpha_0 + Dummies_{y,d,b} + \beta_p \cdot \ln p_{t'}^d + \beta_r \cdot \ln r_{t'}^d + New\ variables \quad (4)$$

$$(1) New\ variables = \sum_{h=1,2,\dots,7} \beta_h Dh$$

Table 2. Hotel dummy variables OLS regression weight.

Ind. Var.		Coeff.	Std. Error	Ind. Var.		Coeff.	Std. Error
<i>Constant</i>		0.424 ***	0.099				
<i>D_h</i>	2	-0.602 ***	0.007	1-Dec 31-Dec	-0.025 ***	0.009	
	3	-0.030 ***	0.011	1-Jan 31-Jan	-0.010	0.007	
	4	-0.065 ***	0.012	1-Feb 28-Feb	-0.009	0.007	
	5	0.338 ***	0.011	1-Mar 15-Mar	-0.011	0.007	
	6	0.162 ***	0.010	16-Mar 31-Mar	-0.045 ***	0.008	
	7	0.061 ***	0.009	1-Apr 15-Apr	0.058 ***	0.008	
	<i>D_y</i>	2016	-0.055 ***	0.006	16-Apr 30-Apr	-0.064 ***	0.009
2015		-0.077 ***	0.007	1-May 15-May	0.026 ***	0.008	
2014		-0.087 ***	0.009	16-May 31-May	-0.032 ***	0.007	
<i>D_d</i>	6-Jun 10-Jun	0.016	0.014	1-Jun 15-Jun	0.034 ***	0.007	
	11-Jun 15-Jun	0.017	0.014	16-Jun 30-Jun	-0.036 ***	0.008	
	16-Jun 20-Jun	-0.110 ***	0.013	1-Jul 15-Jul	-0.024 ***	0.008	
	21-Jun 25-Jun	-0.142 ***	0.014	16-Jul 31-Jul	-0.015 *	0.009	
	26-Jun 30-Jun	-0.138 ***	0.014	1-Aug 15-Aug	-0.030 ***	0.011	
	1-Jul 5-Jul	-0.283 ***	0.014	16-Aug 31-Aug	-0.007	0.014	
	6-Jul 10-Jul	-0.486 ***	0.014	<i>ln p_{t'}^d</i>	-0.283 ***	0.017	
	11-Jul 15-Jul	-0.494 ***	0.015	<i>(ln r_{t'}^d)²</i>	-0.002 ***	0.001	
	16-Jul 20-Jul	-0.581 ***	0.015	<i>R²</i>	0.553		
	21-Jul 25-Jul	-0.578 ***	0.015	<i>Adjusted R²</i>	0.552		
	26-Jul 30-Jul	-0.559 ***	0.016	<i>(P-value)</i>	0.000		
	31-Jul 5-Aug	-0.377 ***	0.015				
	6-Aug 10-Aug	-0.099 ***	0.016				
	11-Aug 15-Aug	-0.096 ***	0.016				
16-Aug 20-Aug	-0.093 ***	0.016					
21-Aug 25-Aug	-0.006	0.016					
26-Aug 31-Aug	-0.200 ***	0.016					
1-Sep 5-Sep	-0.263 ***	0.015					
6-Sep 10-Sep	-0.253	0.016					

Source: Own Elaboration

* Significant at the 90% significance level.

** Significant at the 95% significance level.

*** Significant at the 99% significance level.

- (2.1) *New variables* = $\sum_{s=1,2,\dots,7} \beta_s Ds$ where s represents the hotel size
- (2.2) *New variables* = $\sum_{f=1,2,\dots,7} \beta_f Df$ where f represents the average proportion of family customers segment in the specific hotel
- (2.3) *New variables* = $\sum_{i=1,2,\dots,7} \beta_i Di$ where i represents the average proportion of all-inclusive segment in the specific hotel
- (2.4) *New variables* = $\sum_{l=1,2,\dots,7} \beta_l Dl$ where l represents the average length of stay in the specific hotel
- (2.5) *New variables* = $\sum_{w=1,2,\dots,7} \beta_w Dw$ where w is a dummy variable that indicates the hotels has been recently renewed
- (2.6) *New variables* = $\sum_{a=1,2,\dots,7} \beta_a Da$ where a is a dummy variable that indicates the hotels has a spa among its facilities
- (2.7) *New variables* = $\sum_{g=1,2,\dots,7} \beta_g Dg$ where g represents the average online hotel rating

Table 3. OLS regression weight of hotel attributes and demand characteristics variables.

Ind. Var.	Coeff.	Std. Error
Ds	-0.567 ***	0.007
Df	-0.170 ***	0.009
Di	-0.387 ***	0.007
Dl	-0.363 ***	0.006
Dw	0.393 ***	0.005
Da	0.284 ***	0.006
Dg	0.293 ***	0.005

Source: Own Elaboration.

III. Conclusions

Conclusions

The present thesis goes in depth into the revenue management and optimal pricing techniques in the resort hotel sector. Empirical evidence and references on these techniques in conjunction with the evolution of new technologies is more frequent in the airline industry literature, and even in the urban hotel sector literature, but the resort hotel sector own-characteristics and the importance of traditional intermediaries have delayed its development in this sector. This fact makes these topics an interesting field of study. Hence, the main thesis values are the methodological development of an online transient demand function, which allows the assessment of the different demand behaviors and their segmentation in the resort hotel context, and the development of optimal dynamic pricing models that allow the resort hotel revenue maximization; in parallel, the empirical application of these models with the use of real resort hotel data has produced some interesting results.

In Chapter 1 the factors that are able to cause price shifts and variability within the same hotel and/or among hotels are analysed and reviewed. These factors are sources of price variation and differentiation, customer segmentation and pricing optimization in the hotel sector. The main pricing and RM techniques in the hotel sector that appear in the literature, their evolution, and the current state of research are studied, determined and classified.

The development of information and communications technologies and the larger amounts of data available have allowed moving from aggregate pricing studies towards research at an individual hotel level. New technologies and market developments have also contributed to the transformation of pricing processes from inventory controls to a customer-oriented approach, allowing hotels to improve their response to changes in demand while also ensuring more accurate customer segmentation. Finally, the knowledge of demand and its reaction to price variations are key factors in the optimization model with maximum revenue expectations, but the competitor pricing effect on demand is different in the hotel sector to the airline sector due to their specific characteristics. The main conclusions of Chapter 1 point out that current research should focus in-depth on the study of the customer behavior, in order to improve their segmentation, as well as in the role of competitor pricing in the optimization process, particularly at individual hotel level. In addition, the revenue managers should consider the pricing threshold time effect on hotel performance as another factor in the decision-making process.

In Chapter 2 a particular demand function model for resort hotels for measuring their own-price elasticities of the online demand, along with the different seasonal demands, and across the booking horizons is proposed. A critical step for the RM department, in its bid to maximize revenue, is to estimate demand response to price variations, particularly in the case of the resort hotel sector, which is increasingly impacted by the emerging online transient segments. Thus, it is essential to identify different price sensitivities throughout different seasonal demands and across booking horizons in order to set the right price at the right time, especially at the property level

when the objective is to maximize revenues with the traditional RM tools. Hence the aim of the study in Chapter 2 is three-fold: (1) to present a particular demand model easily adaptable to different hotels; (2) to show an empirical application in two Majorcan resort hotels, describing the data transformation, simplification, and harmonization process of hotel variables used in the model; and (3) to present an analysis and comparison of the model outcomes and elasticities across the different booking times, seasonal demands and between the two hotels.

Conclusions from Chapter 2 indicate that the resort hotel demand estimation not only is able to help the RM departments to set the best price at each point in the booking horizon (short-term), thus maximizing revenue, but it can also help to define the best strategy for each hotel in the medium-term. More specifically, the elasticity values that present both hotels indicate that demands are not so inelastic as those values gathered in the hotel demand literature show. In addition, the results show that the two hotels display completely different own-price elasticities during peak season, while during low season, demand is quite inelastic at both hotels.

In Chapter 3 the online transient demand functions from Chapter 2 are applied to deterministic and stochastic dynamic models in order to determine the prices that maximize the revenues of the last two resort hotels. Both models, through the demand functions, consider the demand response to price variation, as well as the seasonal and the booking date effects. The theoretical basis of optimal dynamic pricing is explained by the limited capacity of a hotel establishment and the expectations of selling the same room at a higher price at a later moment across the booking horizon. More specifically, the deterministic models set the prices that allow for revenue maximization along the booking horizon, while the stochastic models captures the random fluctuations of demand and allow them to differ from average demand. Hence the aims of the analysis in Chapter 3 are to adapt and apply the deterministic and stochastic dynamic pricing models, both very extended in the literature, and to provide an empirical comparison of both models for the emerging online transient segment in two Majorcan hotels.

The main conclusions from Chapter 3 are that both models (deterministic and stochastic models) meet the objective of defining the optimal price for obtaining maximum hotel revenue. In the present chapter the deterministic dynamic models usually produce more optimistic forecasts in terms of hotel revenue estimations, as the average revenue obtained from the last three seasons is higher than the last year revenue, and the stochastic estimations are usually more similar to the latest observed data. Additionally, results also show that not only the price elasticity of demand distribution along the booking horizon and the seasonality affect optimal prices, but also the number of rooms available, the hotel location, and the tourist profile significantly affect optimal prices.

Finally, in Chapter 4, using the demand function model developed in Chapter 2, we estimate online transient demand functions during high season for seven 4-star resort hotels located in different Spanish destinations (Majorca, Tenerife and Andalusia) and compare the different own-price elasticity values. The main objective is to explore the different elasticity values on the different tourism destinations, seasons and booking

horizons; however, other assets, such as the hotel location, specific hotels attributes and customers characteristics, can also explain the differences in elasticities among hotels and tourism destinations. As we mentioned above, the demand function estimation is one of the best methods for measuring these issues in order to determine and compare the different consumer behaviours and their willingness to pay.

The main conclusion from Chapter 4 is that most of the high season periods present elastic demands, but hotel factors such as the hotel renovation, the supply of additional facilities and services, the belonging to the couple and/or half board customer segments, and the higher the proportion of German tourists turns the demand more inelastic. It is also worth of mentioning that during the closest booking periods to the date of stay demand is usually more elastic; the number of local competitors has the power of pushing down hotel price levels; and the peak season usually displays the most inelastic demands, as the hotels located in Tenerife present the most price-elastic demand during the Spanish high season, which takes place in winter time in the island.

The present thesis has proved that customer behaviour segmentation and optimal dynamic pricing are able to improve the resort hotel revenue. All the models developed in the thesis, with their empirical applications, have validated that these can be applied to the resort hotel sector with a positive impact on the hotel RM department. Furthermore, the different pricing policies and revenue maximization processes should be implemented at the individual hotel level, according to their individual characteristics and their specific demand features, more than the own-destination characteristics. Meanwhile, the main limitation is the data availability, as additional data could help to improve all the models estimations, such as information on competitors' prices, booking information referred to the number of guests, room type, board or cancellation policies, and the inclusion of the tour operator segment in the models.

IV. ANNEX

Optimal Pricing in Different Spanish Resort Hotels

The annex section includes the demand functions obtained by Vives and Jacob (2018-b) and implement the optimal pricing deterministic model used by Vives and Jacob (2018-a) in order to squeeze the data obtained during the present thesis. The data and methodology section summarizes the hotel information, as well as the different models used in the previous papers (Vives et al., 2018 and Vives and Jacob, 2018-b), and the results section describes and analyzes all the optimal prices estimated and compares them with the elasticity values and the observed data.

1. Data and methodology

The present study uses the same data as in Vives and Jacob (2018-b), data on seven 4-star hotels belonging to the same multinational hotel chain, two of which are located in Majorca, two in Tenerife, and the last three are located in Málaga, Cádiz, and Huelva (Andalusia region). The revenue management (RM) department of the hotel chain provided the seasonal and booking time online transient bookings and prices. Data used goes from the final of June to the beginning of September, i.e., data on the typical Spanish high season.

Regarding the methodology, the demand function specified is a Cobb-Douglas formulation which can be linearized with the application of natural logarithms (as in Vives et al., 2018; Vives and Jacob, 2018-b).

$$\ln q_{t'}^d = \beta_0 + Dummies_{y,d,bp} + \beta_p \cdot \ln p_{t'}^d + \beta_{RES} \cdot \ln r_{t'}^d$$
$$Dummies_{y,d,b} = \sum_{y=1,2,\dots,Y} \beta_y Dy + \sum_{d=1,2,\dots,D} \beta_d Dd + \sum_{b=1,2,\dots,B} \beta_b Db$$

Where q represents the average number of daily room reservations for each period of time when prices (p) are not changed by the revenue manager over the booking horizon, r represents the distance between the booking time and the date of stay, t' represents the reservation dates over the booking horizon, i.e., the period of time where p remains constant, and the *Dummies* include variables such as the year when the observation takes place (y), the date of stay (d) and the booking period (b).

In each group of dates of stay two different demands are estimated (as in Vives et al., 2018): the first period (Per I), the farthest dates across the booking horizon before the date of stay, usually presents low levels of bookings and lower prices (early booking discounts); and the second period (Per II), the closest dates to the date of stay across the booking horizon, where prices and booking generally increase.

Then, the two demand functions are introduced in the price optimization deterministic model presented by Vives and Jacob (2018-a) in order to estimate the prices that will

maximize the hotel revenue for each date of stay (Aziz et al., 2011; Badinelli, 2000; Guadix et al., 2010; Lee, 2011):

$$R(t') = \text{Max} \sum_{t'} Q_{t'} \cdot p_{t'}$$

When we multiply the number of online transient reservations ($Q_{t'}$) by the price ($p_{t'}$) we can obtain the number of average daily room reservations ($q_{t'}$) that maximizes the revenue obtained along the booking horizon t' .

More specifically, a Lagrange multiplier method is used in order to estimate the prices and bookings along the booking horizon that maximize the revenue:

$$\text{Max } R(t') = \sum_{1,t'} Q_{1,t'} \cdot f(q_{1,t'}, r_{1,t'}) + \sum_{2,t'} Q_{2,t'} \cdot f(q_{2,t'}, r_{2,t'})$$

$$\text{s.t. (1)} \quad \lambda_1: \sum_{1,t'} Q_{1,t'} + \sum_{2,t'} Q_{2,t'} \leq r$$

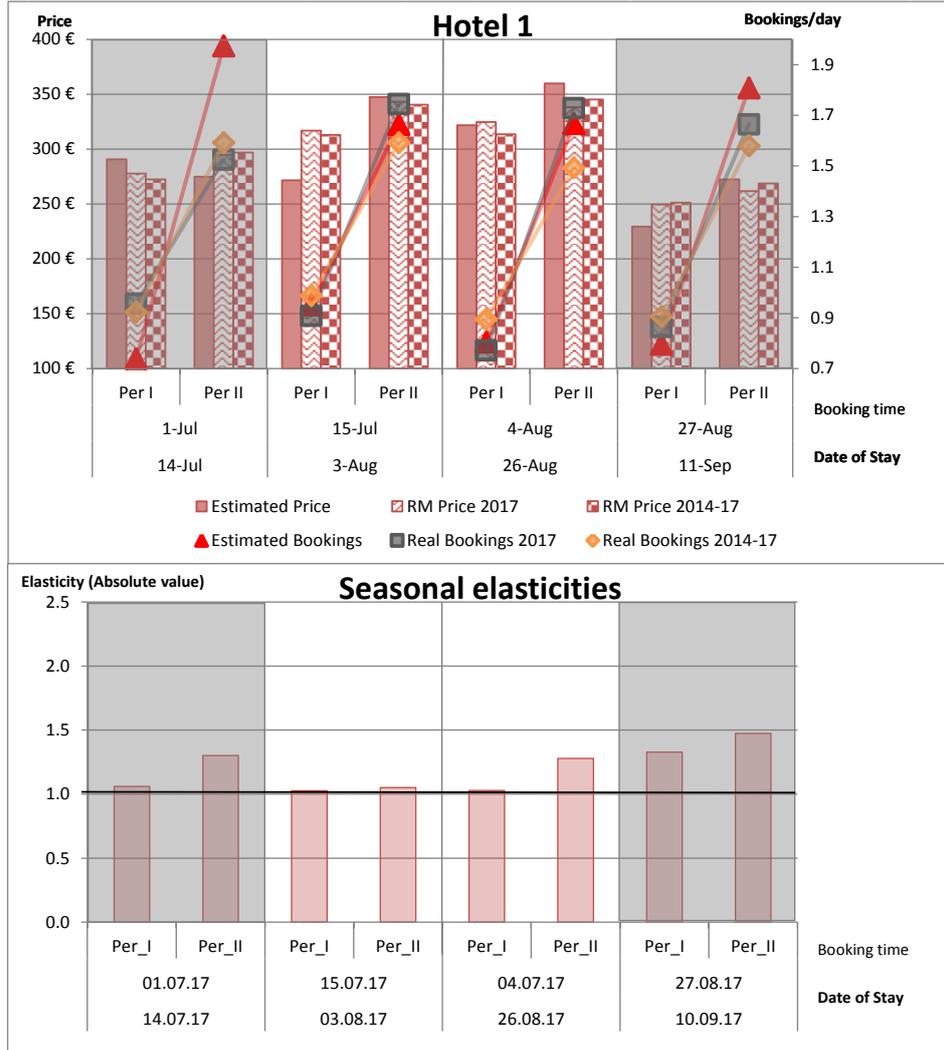
which is subject to the number of rooms r the revenue manager is willing to sell (s.t. 1); the maximum number of rooms that can be sold is the hotel capacity.

2. Results and conclusions

The results summarize the optimal pricing and bookings estimations of the seven hotels, and shows a comparison with the observed prices (RM prices from 2017 and average RM prices 2014-17) and reservations (Real bookings from 2017 and average Real bookings 2014-17), and presents as well the price elasticity of demand values.

The *hotel 1* is located at the North area of Majorca Island, it has 360 rooms, focuses on the couples and half board segments, and the majority of tourists come from Germany. From the estimations of *Figure 1* it can be highlighted that the main recommendation is to reduce prices during Per I and to increase them in Per II. During the peak season (from 15th July to 26th August), when seeking the revenue maximization, the estimations obtained lead to recommend to slightly increase the bookings in Per I and maintain reservations in Per II. In general, high season demands are slightly elastic, while there exist small differences between the elasticity values in Per I and Per II, but the Per II demands are usually more elastic. In parallel with the elasticity values, the prices do not significantly vary among the seasonal periods included in the study. Finally, no large differences among estimated Prices, RM Prices from 2017, and the average RM Prices from 2014-17 are observed.

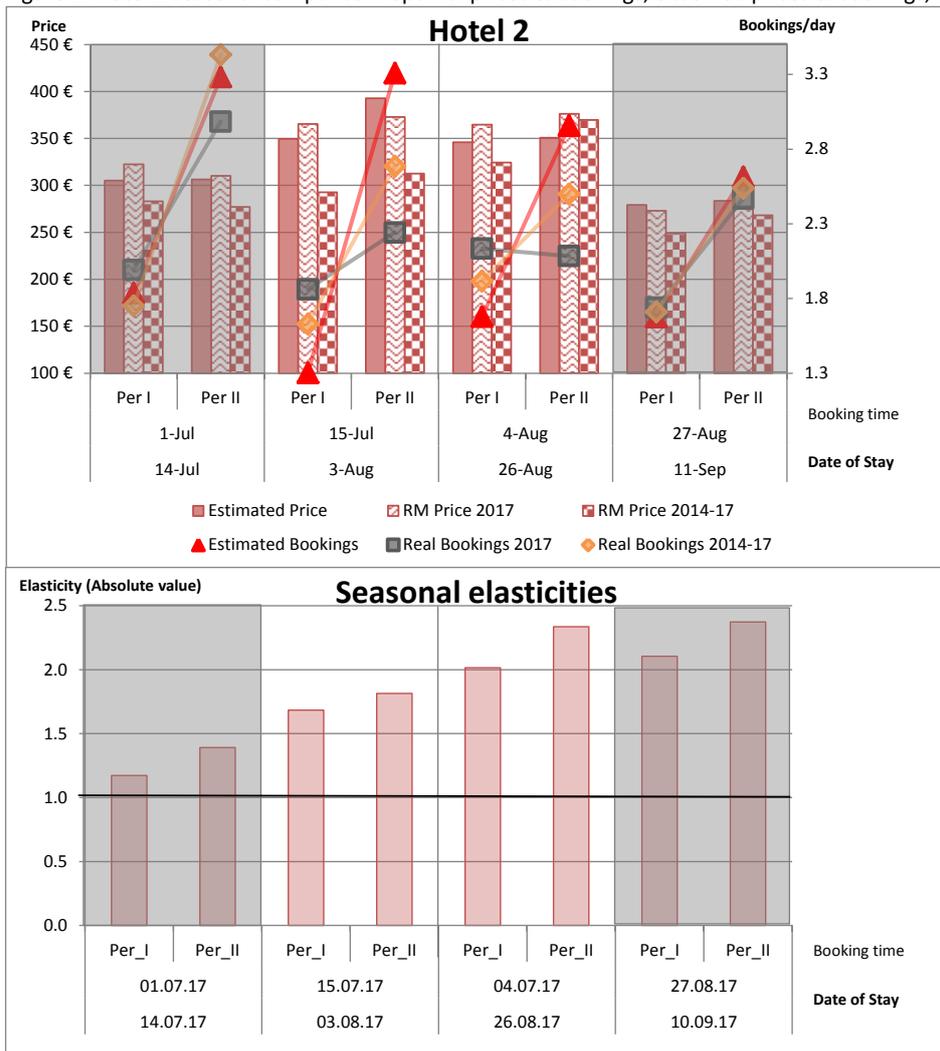
Figure 1. Hotel 1 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

The *hotel 2* is located at the Southeast area of Majorca Island, it is the largest hotel of the sample with 619 rooms, it focuses on the family segment and the majority of tourists book the all-inclusive board and come from the UK. *Figure 2* shows that, excluding the second half of July, the general tendency is the price convergence between Per I and Per II, in order to reduce the level of bookings in Per I and significantly increase reservations in Per II. Regarding the second half of July, it is recommended to reduce prices and restrict the bookings in Per I, while to increase prices and reservations during the Per II. In general, the estimations obtained lead to recommend to moderate prices during the most elastic seasonal periods, as the elasticity level increases the price levels tend to be reduced compared with RM Prices 2017 (15th Jul-3rd Aug vs. 4th Aug-26th Aug periods). Finally, the price tendency of the last seasons has been increasing prices, as the average RM Prices from 2014-17 are significantly lower compared with RM Prices from 2017, which are quite similar with estimated Prices.

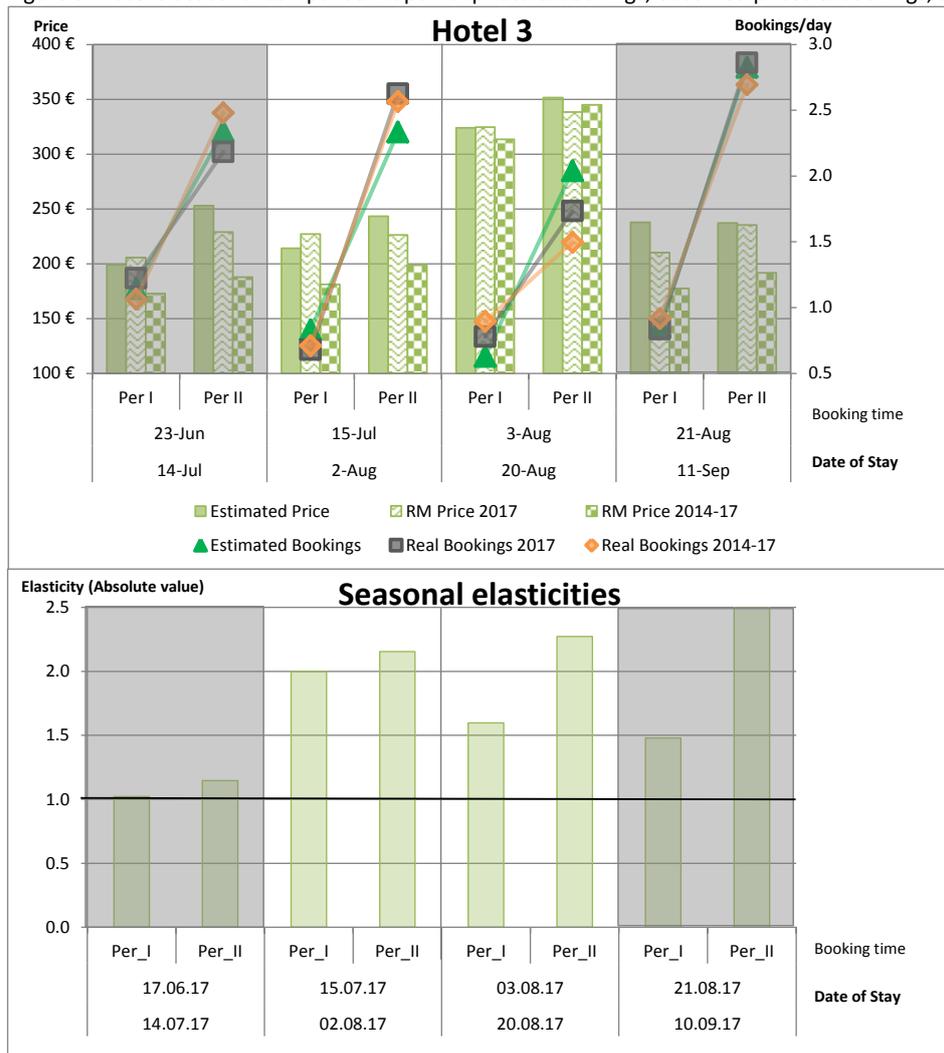
Figure 2. Hotel 2 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

The *hotel 3* is located at the South area of Tenerife Island, it has 404 rooms, focuses more on the couple segment, all-inclusive board is chosen in almost all the reservations, and almost half of tourists come from the UK. In general, *Figure 3* exhibits that in Per I the estimations recommend to contain prices, while in Per II the suggestion is to slightly increase prices. Nevertheless, Per II demand is usually more elastic than the first period, while the general recommendation is to increase prices during Per II, the main explanation is that the weight of the booking time is higher than the elasticity effect in the demand functions. In this specific case, as the elasticity values differences are higher between Per I and Per II, the closer are the estimated Prices and RM Prices from 2017, so the inelastic demand makes the estimations differ from the RM pricing. Finally, the price tendency of the last seasons has been increasing prices, as the average RM Prices from 2014-17 are significantly lower compared with RM Prices from 2017, which are closer to the estimated Prices.

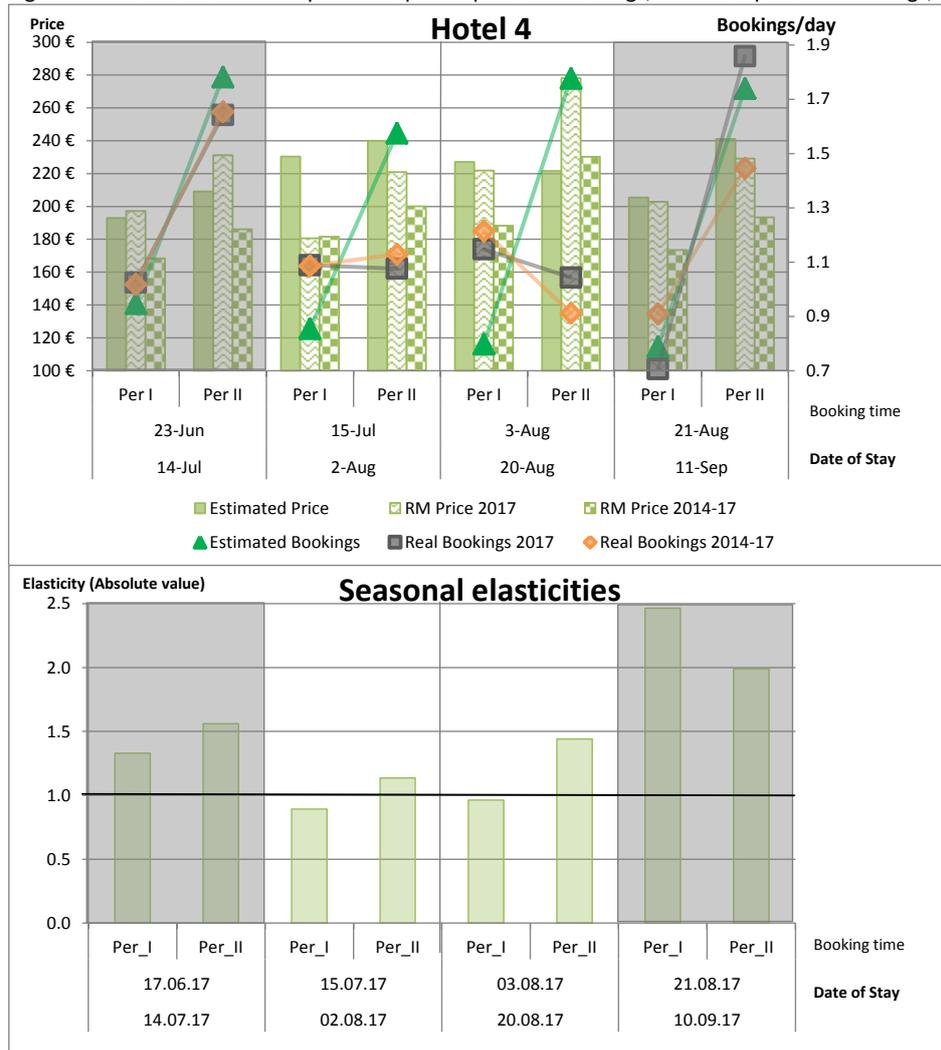
Figure 3. Hotel 3 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

The *hotel 4* is also located at the South area of Tenerife Island, it is the second largest hotel with 505 rooms, focuses on the couple and half board segments, and most of tourists come from the UK. Although the RM Prices from 2017 significantly vary across the seasonal periods, the estimated Prices suggest the price convergence (*figure 4*). Additionally, it is also recommended to maintain the same prices in Per I and Per II, except for the last seasonal period (21th Aug-11th Sep), where the suggestion is to increase prices in Per II. The estimated prices are consistent with the elasticity values, during the first three seasonal periods (23th Jun-20th Aug) the demands are more inelastic and Per II is slightly more elastic compared with Per I, while in the last seasonal period (21th Aug-10th Sep) the demand leads to more elastic values and Per I elasticity increases over Per II. In general, the estimated prices are significantly different to the observed prices (RM Price 2017 and RM Price 2014-17), while the observed prices are equivalent to the *hotel 3* prices, which could indicate an erroneous pricing strategy in *hotel 4*. Finally, it has to be highlighted that the tendency of the last seasons has been to increase prices, as RM Prices from 2017 are significantly higher compared with average RM Prices from 2014-17.

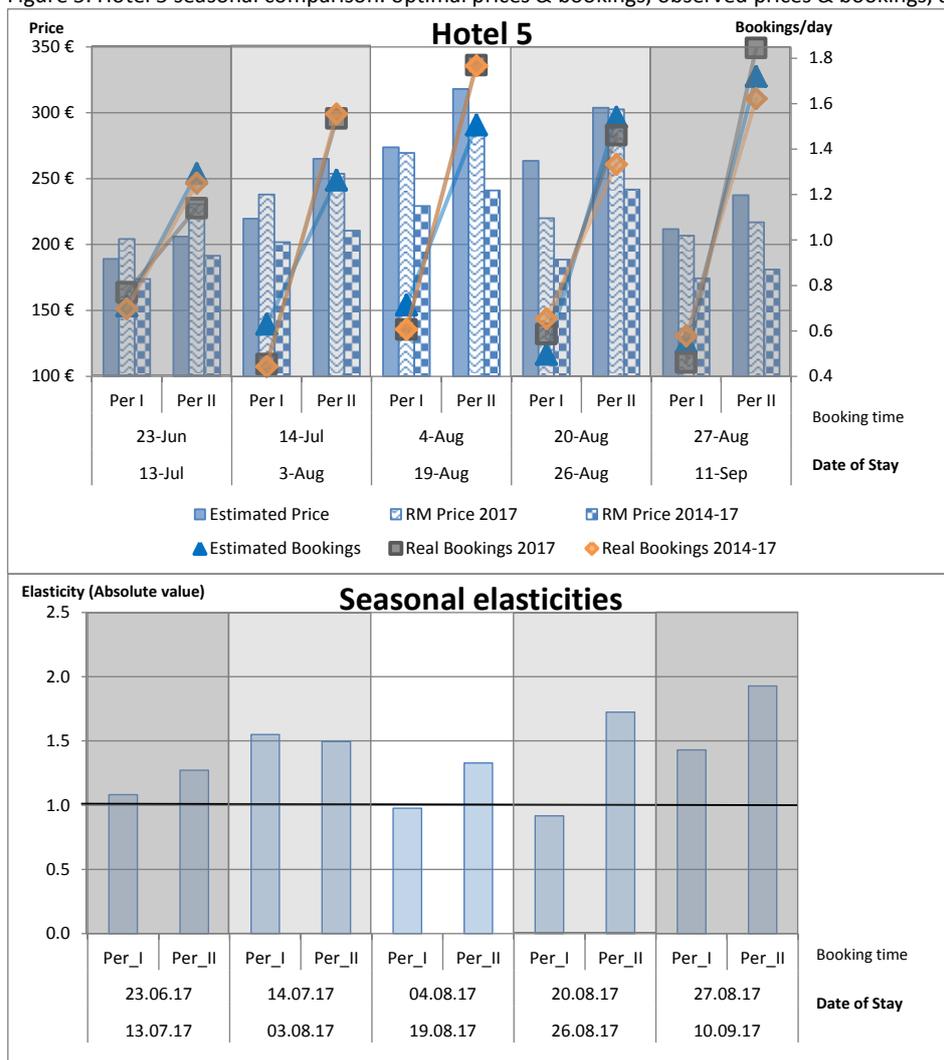
Figure 4. Hotel 4 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

The *hotel 5* is located in Chiclana (Cádiz), it has 413 rooms, focuses more on the couple segment, it shares a similar proportion of all-inclusive and half board reservations, and most of the tourists are Spanish. In general, the estimations from *Figure 5* indicate that in Per I the general recommendation is to keep or slightly lower prices and to increase bookings, while to increase prices and maintain bookings stable in Per II. The peak season (4th Aug-19th Aug) is the most inelastic seasonal period and the suggestion is to raise prices, while in the most elastic seasonal period the results recommend to slow down the price increase. Finally, the general tendency has also been a price rise, as RM Prices 2017 are higher than average RM Prices 2014-17.

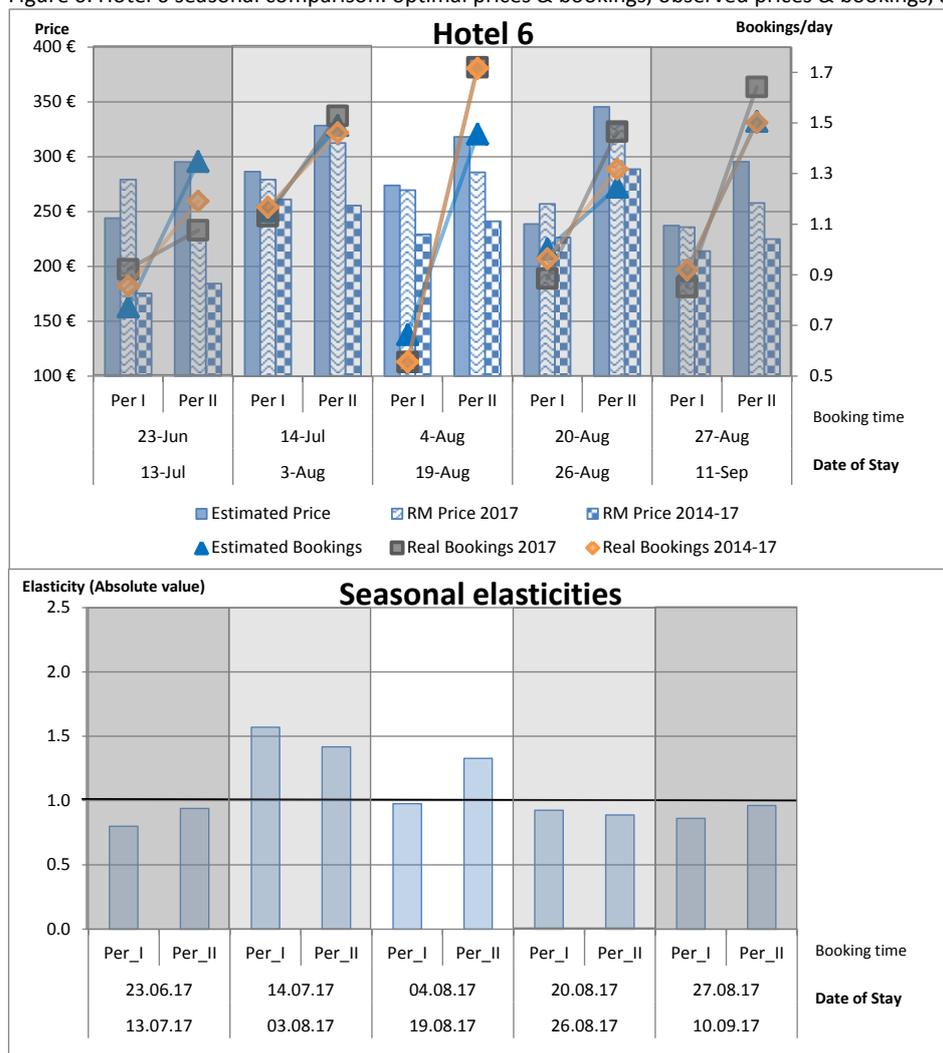
Figure 5. Hotel 5 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

The *hotel 6* is located in Torrox Costa (Málaga), it also has 413 rooms, focuses more on the family segment, shares a similar proportion of all-inclusive and half board reservations, and most of the tourists come from Germany. Unlike what happens with *hotel 5* estimations the tendency of *hotel 6* for the main high/peak season (from 14th Jul to 26th Aug) is to match prices among the different seasonal periods (*Figure 6*). During the inelastic and unit-elastic periods the results recommend in Per I to hold prices stable and to increase bookings, while in Per II to significantly increase prices and reduce reservations. It is worth pointing out that the most elastic seasonal period (14th Jul-3th Aug) presents the lowest differences between the estimated Prices and the RM Prices 2017. Finally, the price tendency has been to slightly increase prices (RM Prices 2017 vs. RM Prices 2014-17).

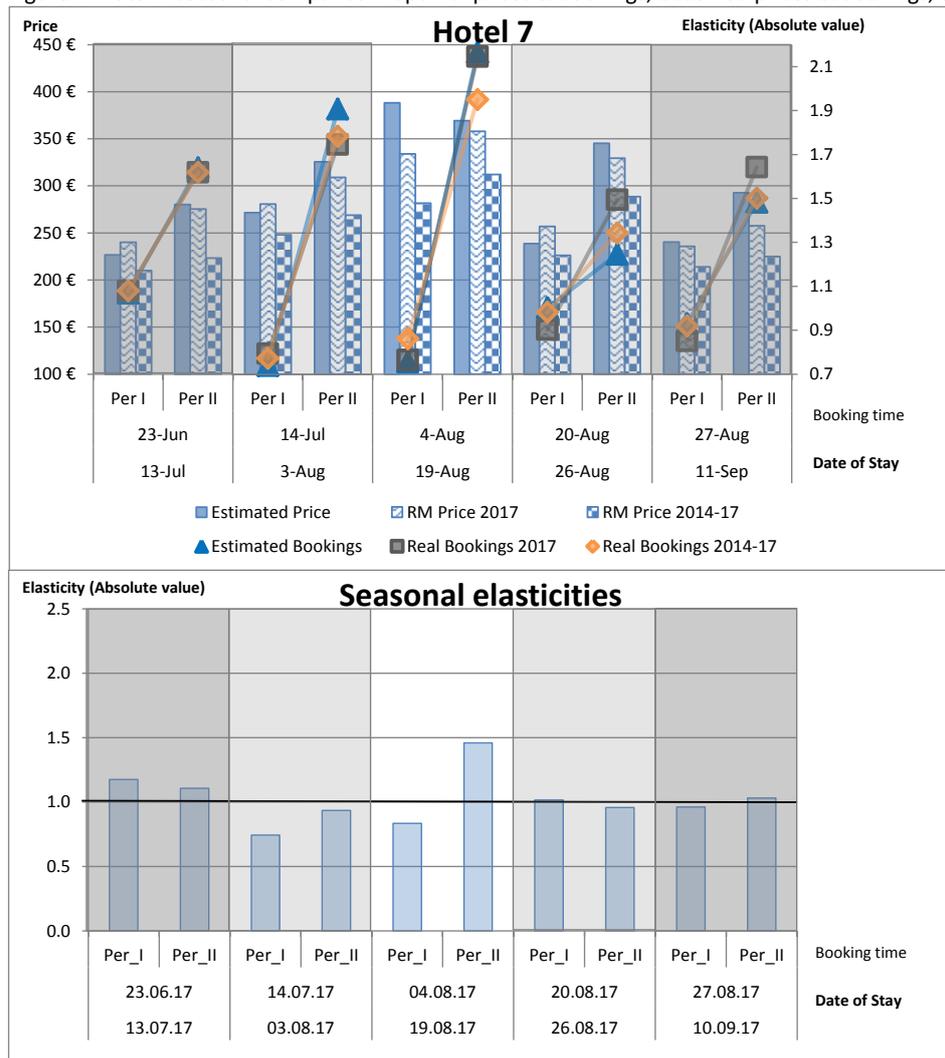
Figure 6. Hotel 6 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

The *hotel 7* is located in Ayamonte (Huelva), it is the smallest hotel with 300 rooms, it focuses more on the family and all-inclusive segments, and most of tourists are Spanish. The estimations from *Figure 7* indicate that in peak season (4thAug-19thAug) prices should be increased, especially by raising the Per I prices over the Per II prices, and at the same time maintaining the bookings constant in both periods. In the rest of seasonal periods the recommendation is to reduce prices and to slightly increase bookings in Per I, while to raise prices and moderate the reservation levels in Per II. In general, *hotel 7* demand is significantly inelastic in high season periods and the estimations recommend increasing prices because it will have a low impact on the booking levels. The price tendency is also increasing during the last seasons (RM Prices 2017 vs. RM Prices 2014-17).

Figure 7. Hotel 7 seasonal comparison: optimal prices & bookings, observed prices & bookings, and elasticities.



Source: Own elaboration and Vives and Jacob (2018-b).

To sum up, the hotels located in the same destination follow similar pricing policies, due to the fact that in the hotels chains it is usually the same person the one who manages the nearby hotels. Meanwhile, the results show that hotels located in the same destination should follow individualized pricing policies, more focused in the specific hotel and tourists characteristics, as indicated by Vives and Jacob (2018-b).

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