A COMPARISON OF DESTINATIONS' IMPACTS ON HOTEL RATES

Abstract

The impact of destinations' attributes on hotel rates in different locations has been insufficiently compared the existing literature. This study sought to apply the hedonic pricing method to measure and compare how room prices are affected by factors that are both external and inherent to hotel companies. After collecting nearly all the data regarding hotel features that consumers can use to make choices about accommodations on the TripAdvisor website, different models were developed for each city and season. The results suggest that hotels in Barcelona are more dependent on external conditions than hotels in Madrid are. In addition, hotels in both cities are more affected by external conditions during the high season. This paper discusses these and other results, as well as their implications.

Keywords: Barcelona; destination; external dependency; hedonic price model; Madrid; TripAdvisor.

1. INTRODUCTION

Because a strategic location is crucial to any hotel's success, clear connections exist between each hotel and the surrounding destination (Yang, Wong, & Wang, 2012). The profitability of hotels thus heavily depends on the market structure and popularity of tourist destinations (Lado-Sestayo, Otero-González, & Vivel-Búa, 2016). Given increasing market saturation, hotels must be located near popular tourist destinations to remain competitive (Assaf, Josiassen, Woo, Agbola, & Tsionas, 2017). The occupancy rate of tourist destinations is the single most important factor in determining hotels' survival according to Lado-Sestayo, Vivel-Búa, and Otero-González (2016). Hotels' occupancy rates, in turn, are extremely important to their success (Viglia, Minazzi, & Buhalis, 2016).

The task of positioning destinations in the market, promoting them, and coordinating efforts among different stakeholders falls to destination management organizations (DMOs) (Prideaux & Cooper, 2002), whose achievements are measured by indicators. These include the number of tourists (Archer & Fletcher, 1996)—a key variable commonly linked to DMOs and destinations' success (Bornhorst, Ritchie, & Sheehan, 2010)—and tourist expenditure, as well as other destination measures, such as satisfaction levels (Fuchs & Weiermair, 2004; Kozak & Rimmington, 1999).

These factors affect guests' satisfaction with hotels (Bulchand-Gidumal, Melián-González, & Lopez-Valcarcel, 2013), as do other destination features, including seasonality (James & Tom, 2002), climate (Chen & Lin, 2014; Day, Chin, Sydnor, & Cherkauer, 2013), and crime rates (Assaf, Josiassen, & Agbola, 2015). However, revenue per available room (RevPar), together with occupancy ratios, is particularly important to hotels' financial success (Bornhorst et al., 2010). Some researchers emphasize both RevPar and hotels' ability to adapt to ever-changing circumstances as strategic tools for survival (e.g., i Baidal, Sánchez, & Rebollo, 2013).

Thus, the extent to which hotels are dependent on destination attributes needs to be determined to help managers enhance hotel profitability (see, for example, Assaf et al. [2017]). These attributes are broadly understood to include, among others, public goods and services, complementary tourist attractions, competition levels, and destinations' brand equity compared to their competitors. A further relevant factor is the time conditions imposed on reservations (i.e., the specific date on which reservations are made and the booking margin).

In this context, it is important to bear in mind that, first, destination features are not controlled by hotels, but both hotels and other lodging establishments seek to exploit these features. Second, destination characteristics attract visitors, while hotels profit from such features because these firms can charge higher rates. However, improvements in destination features not only increase the price of accommodations but also attract more competitors to well-managed destinations.

Therefore, a worthwhile research objective is to determine the degree to which hotels are dependent on destination attributes. The present study sought to measure this dependency by comparing two leading Spanish tourist destinations: Madrid and Barcelona. The well-known hedonic pricing method was selected as the most appropriate for this research.

The hedonic pricing method has had a long and fruitful relationship with research on both tourism and the hotel business because this model is best used to investigate unique markets (Palmquist, 2005). These markets are part of research on destinations since they can be understood as geographic areas with a distinct image (Buhalis, 2000). This field of research has already produced a large body of literature, drawing together specific findings to create a broad picture of the hospitality business. For example, the results of hedonic pricing research show that the variables that exercise the greatest influence on hotels' prices are their category and location (Abrate, Capriello, & Fraquelli, 2011). According to Costa (2013), these prices are primarily determined by various tangible factors including not only hotel

category and geographic location but also type of accommodation and membership in hotel chains.

A brief review of the literature on hotels and a presentation of the conceptual framework follows in the next section. The third section briefly explains the theoretical framework of the hedonic pricing model applied, describes the methods used to create the database and collect the data, and discusses the two cities' descriptive statistics. The fourth section presents the main results, which are then discussed in the fifth section. The conclusions are presented in the last section.

2. CONCEPTUAL FRAMEWORK

One method of measuring the dependency between hotels and destinations is to use hedonic prices because destinations' characteristics are among the features incorporated into hotel room rates, accounting for part of these prices (Rigall-I-Torrent & Fluvià, 2011). This method can be applied to determine how much room prices can be explained by hotels' own activities and by factors extrinsic to these establishments. The resulting information could answer the question of how much hotel room rates are determined by destination characteristics, as was found to be the case in a study conducted by Bulchand-Gidumal et al. (2013), which focused on guest satisfaction.

A review of the literature for the present study revealed that attributes can be categorized by hotels' degree of control over these features (Yang et al., 2016), including grouping factors as internal and external (Chen & Rothschild, 2010). Although the first category is not bounded, its inclusion in most studies has resulted in a quite well-defined profile of what hotels can control. In contrast, identifying external factors is a complex task (Yang et al., 2016). This is due to the large number of attributes that can come into play, depending on the specific objectives pursued by researchers and hotels' dependency on external factors in the destinations under study. Therefore, for the purposes of the present

study, external factors were assumed to be destination attributes understood in their broadest sense, as mentioned previously.

Comparing the impact of factors in different destinations, moreover, can be especially complicated because markets need to be analyzed individually when using the hedonic pricing method (Palmquist, 2005). Assessing different models can be challenging due to their sensitivity to choices of functional form (Haab & McConnell, 2002) and parameter identification (Ekeland, Heckman, & Nesheim, 2004). The present study thus focused on measuring the impacts of hotels' attributes, as these are reflected in data gathered from TripAdvisor, and the attributes' explanatory power. The assumption was made that the rest of any price variance can be explained by factors considered external to hotels, again in the broadest sense of the word.

Based on a review of research on the lodging sector using hedonic price models—including all those identified by Assaf et al. (2017)—the factors considered external were defined as all those conditions affecting prices over which hotels have no control. These factors can include macroeconomic conditions in tourists' countries of origin and destination, tourism regulations, levels of competition, and destinations' life cycle. Other factors are the assets the public associates with specific destinations. These can be material goods, such as infrastructure or physical and natural heritage, or intangible assets, such as security, destination brand, destinations' capacity to attract visitors, quality of tourism services, or high-impact events.

Therefore, the present study assumed that no additional variables outside of those listed by TripAdvisor significantly condition prices. This approach comes close to being an oversimplification of reality since, for example, researchers have confirmed that hotels' age can condition room rates (Hung, Shang, & Wang, 2010). However, this factor is not included on TripAdvisor. To test the present research's conceptual framework, virtually all the

quantitative information available on TripAdvisor was collected. Thus, the information used in this study is essentially the same as that used by potential users, outside of reviews written by other travelers.

This approach was chosen for several reasons. The first was, as previously stated, that destinations' diversity makes comparison difficult. In contrast, hotel features can be measured in a homogeneous and easily comparable way that excludes the particularities of each destination, resulting in equivalent models with respect to functional form and parameters. The second reason was that the literature on hedonic pricing has primarily focused on hotel features. As a result, the impact of hotel attributes can be more easily measured than the impact of destination features. The results of this study could also be more easily compared with others in the literature if the analyses focused on hotel attributes. The last reason was that the selected methodology facilitated the measurement of hotels' dependence on destination attributes without having to go into detail about these attributes.

To maximize the number of hotels included in the hedonic regression, the prices used were extracted from the price range listed for each hotel on TripAdvisor. In this way, the use of hotels' data did not depend on the specific date on which the search was conducted or the room availability on a particular day. These prices were thus equivalent to the list prices used in several previous studies using hedonic pricing (Israeli, 2002; Papatheodorou, 2002; Thrane, 2005). According to Israeli (2002), rack rates can be used, first, as indicators of quality or brand images generated by hotels—positioning hotels in the industry and among consumers. Second, the prices are judged individually and simultaneously so that no price is the direct result of another hotel's advertisements and promotions. However, as noted by Israeli (2002), list prices are commonly criticized as not reflecting true market prices.

In contrast, the range of prices on TripAdvisor is based on actual market prices. This has the three advantages of (1) showing the selected hotels' market position based on real

actions, (2) maximizing the number of hotels present in the sample because their data do not depend on the availability of rooms at a specific time, and (3) reflecting market prices. However, the disadvantage of using this type of price is that it does not differentiate between weekday and weekend rates or consider the booking margin.

In addition to prices, other information was collected based on the findings of the literature review. Virtually all studies based on this method include hotel category measured by number of stars as a factor—with some exceptions such as Thrane (2007). The existing research shows that category has a significant, positive impact and, in some cases, that it is the most important factor in determining hotels' pricing policies (Israeli, 2002; Schamel, 2012).

The present study used hotels' number of rooms as a proxy for hotel size. The latter variable has produced mixed results in the literature. Israeli (2002) and de la Peña et al. (2016) report a positive correlation. Saló, Garriga, Rigall-I-Torrent, Vila, and Fluvià (2014); Soler and Gémar (2016); and Zhang, Zhang, Lu, Cheng, and Zhang's (2011) studies found a negative correlation, while Agmapisarn's (2014) results reveal no significant correlation. These varying results reflect destinations' impact on tourists' willingness to pay. That is, while hotel size is a strictly internal choice, the destination in question and, more specifically, visitors' characteristics condition their willingness to pay for these attributes. In addition, data on membership in a hotel chain were collected for the present study (Aguiló, Alegre, & Sard, 2003; Lee & Jang, 2011; Thrane, 2007)

All previous studies have included hotel location as a factor, measured either in terms of distance from a point of reference (Herrmann & Herrmann, 2014; Lee & Jang, 2011; Schamel, 2012) or location or non-location in a particular area (Andersson, 2010; Chen & Rothschild, 2010; de la Peña, Núñez-Serrano, Turrión, & Velázquez, 2016). Other studies have applied a combination of both approaches (Abrate et al., 2011; Aguiló et al., 2003;

Alegre, Cladera, & Sard, 2013). Guests' ratings of hotel locations have also been used as a measure of this feature's value (Soler, Gémar, & Sánchez-Ollero, 2016).

Given the above research, the present study also considered hotels' distance from the city center (Schamel, 2012). The latter variable was used in its logarithmic form because this distance does not follow a linear pattern. The data on a series of other location-related variables, such as labelled locations or neighborhoods identified by TripAdvisor, were also collected (Andersson, 2010; Chen & Rothschild, 2010; de la Peña et al., 2016). Logically, these locations differ for the two cities, with the exception of the city center label, which is present in both cases.

These location variables were incorporated in the model for various reasons. First, both distance to the center and the presence of hotels in specific neighborhoods correspond to decisions made by hotels, which are part of their overall strategy and which involve specific costs (e.g., property and rental expenses). Therefore, although these factors could be interpreted as external—the literature generally conceptualizes them in this way—they result from conscious decisions by hotel managers at the time their hotels are set up in the destination. The location is fixed at that time (Bull, 1994) rather than being spontaneously or randomly generated by the destination, so these data were integrated as variables in the analysis of internal hotel attributes.

The inclusion of location variables is supported by the nature of TripAdvisor's average prices. These prices are free of uncontrolled variations caused by dissonant elements such as conferences, sporting events, and fairs. Therefore, these location features correspond more closely to strategic assets linked to hotels' location-based services and business model than to specific events that may occur in destinations at specific times. The present research thus assumed that hotels invest part of their resources in this area.

The second reason these variables were included was that the non-inclusion of an important variable such as location could result in omitted-variable bias, which can be of significant concern in hedonic models due to inconsistent coefficient estimates (e.g., Chay & Greenstone, 2005; Figlio & Lucas, 2004; Pope, 2008). To avoid omitted-variable bias in these models, enough control variables must be introduced (Abbott & Klaiber, 2011; Hua & Yang, 2017; Zabel, 2015). Therefore, the core importance of location variables affecting hotel room rates lay in keeping this bias's effects under control in the present research.

Third, in line with the previous point, the inclusion of location variables satisfies the need to make the current results comparable to those reported in much of the literature. The non-inclusion of location variables could complicate any comparison of the present results with the state of art in the field. This issue stems from the previously mentioned sensitivity to the choices of functional form (Haab & McConnell, 2002) and parameter identification (Ekeland et al., 2004).

Last, including all these data helped to ensure the current study also contributed to improving the decision-making processes of hotel managers of both destinations under study. As mentioned earlier, tourists' willingness to pay for each attribute depends on the destination in question, so most of the literature has been based on individual destinations' results. The present research sought to provide insights that can guide hotel managers in Madrid and Barcelona by including data on hotel locations' distances and the specific names of neighborhoods.

Soler et al. (2016) also focused on the cities of Madrid and Barcelona, evaluating the impact of being an environmentally responsible hotel has on room rates. Various other studies regarding hotels' commitment to environmental responsibility and sustainability have used hedonic pricing models to assess customers' willingness to pay more for environmentally sustainable hotels in different destinations (García-Pozo, Sánchez-Ollero, &

Marchante-Mera, 2013; Kuminoff, Zhang, & Rudi, 2010; Sánchez-Ollero, García-Pozo, & Marchante-Mera, 2014). This kind of research belongs to a cluster of studies that have evaluated specific aspects of hotels.

For instance, Fleischer (2012) assessed, among other factors, the impact of rooms' Mediterranean Sea views on room rates. De la Peña et al. (2016) used the hedonic method to assess how the innovative attitudes of hotel owners in Cuba influence hotel prices. Pawlicz and Napierala (2017) applied the hedonic price model, among other approaches, to facilitate a comparison of different online travel agents. Soler and Gémar (2016) used the same method to evaluate the impact of being a family-run hotel on prices. These examples demonstrate this model's adaptability to different situations and objectives.

In addition, the ability to manage brand reputation is a key factor in hotels' success. Communication with customers has become a core asset for hoteliers (Xie & Heung, 2012), and some researchers such as Viglia et al. (2016) have suggested that using appropriate reputational management systems increases hotel occupancy and, therefore, overall performance. Hotels must have the ability to respond to customer expectations, as well as manage performance failures (Soler & Gémar, 2017a). The present study thus collected the variables related to reputation included in overall guest ratings on TripAdvisor (Andersson, 2010; de la Peña et al., 2016; Li, Ghose, & Ipeirotis, 2008; Schamel, 2012) and any certificates of excellence awarded from among the certificates of quality available (Abrate et al., 2011; Alegre et al., 2013; García-Pozo et al., 2013; Rigall-I-Torrent et al., 2011; Sánchez-Ollero et al., 2014).

On TripAdvisor, both hoteliers and users can upload photos of their hotels. The best hotels include professional photos and encourage consumers to upload photos of their accommodations to build their online reputations. Other hotels restrict or pretend to delete photos, claiming that they do not correspond to reality. Therefore, the present study also

incorporated the number of photos posted on hotels' TripAdvisor profiles by hotels and customers. This research also considered online labels regarding hotel style that represent how hotels present themselves to consumers (de la Peña et al., 2016). Finally, data on the most important facilities and services that consumers use to filter hotels were gathered (Agmapisarn, 2014; Chen & Rothschild, 2010; de la Peña et al., 2016; Falk, 2008; Kuminoff et al., 2010).

The present approach contrasts with various studies that have focused on the effects of specific aspects of destinations on hotels, which the current research classified as external factors and, therefore, outside the hotels' control. For example, Rigall-I-Torrent et al. (2011) studied how beach characteristics affect hotel room prices. Rigall-I-Torrent and Fluvià (2011) examined the impact of public goods and hotel location. Alegre et al. (2013) found significant differences were associated with guests' country of origin. In the same vein, Hamilton (2007) examined the effect of a coast and other landscape features on accommodation prices using a hedonic price model, while Coenders, Espinet, and Saez (2003) evaluated the effect of climate on room rates. Santana-Jiménez, Sun, Hernández, and Suárez-Vega (2015), in turn, compared the influence of rural destinations on local accommodations in two tourism destinations.

Other authors have found proof of a significant effect on room rates of any imbalance between room supply and demand (Chen & Chiu, 2014) and market accessibility (Yang, Mueller, & Croes, 2016). Some studies have also analyzed the impact of major events on the price of hotel rooms, for example, Hermann and Hermann's (2014) study of the impact of Oktoberfest in Munich and Soler and Gémar's (2017b) investigation of the effects of the April Fair in Seville. Other factors that have been studied include the date reservations are made (Schamel, 2012), the season (Monty & Skidmore, 2003), and the booking margin

(Abrate, Fraquelli, & Viglia, 2012). Table 1 offers an overview of recent empirical hedonic research and the main variables used.

Table 1. Overview of recent empirical hedonic studies

Approach	Focus	Authors	Area	Independent Variables	
				Internal Attributes	**External Attributes**
Internal	Hotel management	Agmapi-sarn (2014)	Bangkok	Hotel age, number of rooms, room size, chain and hotel facilities	Distances (city center and Bangkok Mass Transit System)
		Soler and Gémar (2016)	Malaga	Stars, number of rooms, service rating and family business hotel.	Distance between hotels and city center, booking day and booking margin
		De la Peña et al. (2016)	Cuba	Stars, size, chain, type of room, core target, brand, online rating, amenities and services	Physical location
		Abrate and Viglia (2016)	Historical center of Milan	Stars, number of rooms, size of rooms, online reputation, amenities and services	Number of close competitors and number of other competitors, booking day and booking margin
	Environmental management	García-Pozo et al. (2013)	Andalusia	Stars, chain, survey of managers about environmental involvement, number of quality certification, number of environmental certifications, amenities and services	Physical location

Sánchez-Ollero et al. (2014)	Andalusia	Stars, environmentally sustainable measures initiatives, quality and environmental quality certification and amenities and services	Physical location
Soler et al. (2016)	Madrid and Barcelona	Stars, chain, service rating and green values according TripAdvisor tags	Location rating

	Comparison between types of accommodation	Saló et al. (2014)	Costa Brava	For hotels: number of rooms, stars and hotel facilities For second homes: home attributes and intermediary	For hotels: room location For second homes: sea view For both: season, physical location, distance to the beach and jurisdiction facilities
External	Market conditions	Costa (2013)	Ibiza	Stars, accommodation type, accommodation regime, number of rooms and chain	Physical location
		Chen and Chiu (2014)	Taiwan	Amenities and services, number of guess room, number of housekeeping staff per guest room, occupancy rates	Economic and touristic Taiwanese indicators, distance to airports, Physical location in a metropolitan area, shuttle bus available
		Yang Mueller and Croes (2016)	Caribbean islands	Stars, rating, accommodation regime and amenities and services	Travel costs, periods and beach
	Influence of events	Herrmann and Herrmann (2014)	Munich (less than 10 km from Theresien-wiese)	Stars and online rating values	Distance between hotels and location of Oktoberfest, number of rooms available in the city, booking day, booking margin,
		Soler and Gémar (2017)	Seville	Stars, number of rooms, rating	Booking day, fair day and distance
	Location patterns	Alegre et al. (2013)	Majorca Island	Stars, chain, number of rooms and floors, quality certification,	Physical location, distances (center, beach and airport), beach, quality values, sea view

		amenities and services	and hotel rooms' ratio in the jurisdiction
Pawlicz and Napierala (2017)	Warsaw	Stars, number of rooms, chain	Physical location, distance to the city center, distance to the nearest competitor, distance to the nearest transportation hub,
Soler and Gémar (2018)	Malaga	Stars, number of rooms, customer satisfaction with the value proposition	Location strategy, booking day and booking margin

Source: Authors

3. MATERIALS AND METHODS

Given the preference for this approach reported in the literature, hedonic price models have been used in many studies for almost a century (Fleischer, 2012). Nevertheless, Lancaster (1966) and Rosen (1974) are considered to have developed the precursors of the theoretical principles behind the hedonic pricing method currently in use. Rosen's (1974) hedonic pricing model allows researchers to estimate the implicit prices for the various characteristics and attributes of an overnight hotel stay, which is defined as a vector of these features (Rigall-I-Torrent & Fluvià, 2011). This is possible as long as the data available can be used (Rigall-I-Torrent et al., 2011) to ensure the final room rate corresponds to the sum of the implicit prices of the rate's component characteristics (Schamel, 2012). Rosen's (1974) model has the principal advantage of being based on real market data (Fleischer, 2012).

Rosen's (1974) model assumes the hypothesis of no significant transaction costs and perfect competition, although the latter is not necessary if the first part meets certain other conditions (Falk, 2008). The model also presupposes that buyers have perfect information (Schamel, 2012). The last cited author notes that researchers can assume that consumers have

281 access to perfect information through a metasearch engine such as TripAdvisor. Finally,
282 because the model's data needs to belong to a single market (Palmquist, 2005), most studies
283 that use this hedonic pricing model have focused on a single destination.

284 The general expression of this is given as Equation 1:

285 $$P_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i \quad (1)$$

286 in which P_i is the price of a room at hotel *i*, α is the constant (i.e., intercept), X_{ki} represents
287 the different attributes *k* for each hotel *i*, and β_k is their respective associated coefficients.
288 However, some authors recommend changing the price using the natural logarithm to
289 improve the model's explanatory power (Rosen, 1974; Wooldridge, 2009), based on Equation
290 (2):

291 $$Ln\, P_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i \quad (2)$$

292 The data gathered for the present study facilitated the choice of the functional form for the
293 hedonic price function (Falk, 2008). The transformation of the variables using Box-Cox
294 models improved the explanatory power of the hedonic models overall, especially the price
295 variable (Haab & McConnell, 2002). Following Abrate et al. (2011) and other authors'
296 example, the adequate adjustment of different functional forms framed within Box-Cox
297 models was verified, which facilitated the selection process in the logarithmic transformation
298 of prices. Based on this process, the present study could use Equation (2) to estimate the
299 values using ordinary least squares.

300 The hedonic pricing model is not without issues. Some authors have used alternative
301 methods to ordinary least squares, such as Masiero, Heo, and Pan (2015), who employed
302 discrete choice models, or Masiero, Nicolau, and Law (2015), who used a quantile regression
303 model. Assaf and Tsionas (2018), among others, encourage researchers to use these
304 alternative models in hospitality and tourism research.

In addition, spatial effects are an important issue in destination choice models (Matthews, Scarpa, & Marsh, 2018), and many authors have paid special attention to this issue of hedonic models by ensuring a thorough treatment of important spatial variables (e.g., Kuminoff et al., 2010). Other scholars have examined the spatial implications for prices by combining hedonic price models with more complex models, such as geographically weighted regression models (e.g., Latinopoulos, 2018; Soler & Gemar, 2018; Zhang et al., 2011). Currently, the possibilities offered by big data facilitate analyses even of spatiotemporal patterns of destinations using data from online booking services (e.g., e Silva et al., 2018). Another approach is to assess the impact on prices of variability in time factors using geographically and temporally weighted regression models (e.g., Huang, Wu, & Barry, 2010). Nevertheless, due to the scarcity of previous research comparing the results of these models, the better-known hedonic price model was chosen for the present study.

3.1 Database

All the data were collected from the English version of the TripAdvisor website (i.e., www.tripadvisor.co.uk) in December 2016. The data were collected for all 446 hotels in Madrid and 518 hotels in Barcelona, for which TripAdvisor had information available. However, because some hotels provide only a small entry sheet on TripAdvisor and others did not provide price information, the final number of hotels included in the study was smaller. Thus, the data for Madrid included 362 hotels in the low season and 359 in the high season, whereas the data for Barcelona included 417 hotels in the low season and 418 in the high season.

In addition to prices, almost all the variables available on the website were collected and used in the form that best fits each variable. This methodological choice was far from arbitrary as it reflected a thorough review of the literature on hedonic price models and the need to maintain closer control by selecting the best way to specify each variable. The

functional form of the models used did not differ from the forms most commonly reported in the literature, except for the use of the range of prices provided by TripAdvisor instead of market prices. List prices have been used in previous studies, but they have been less extensively utilized than market prices.

Researchers widely agree that temporary circumstances in destinations affect price levels. The strength of local competition (Becerra, Santaló, & Silva, 2013), booking margin (Abrate et al., 2012), check-in day (Soler & Gémar, 2017b)—if this occurs during the week or on weekends (Schamel, 2012)—or important events in the period under study that alter hotel room rates (Herrmann & Herrmann, 2014) are some examples of these temporary external factors. They were not, however, analyzed in the present study due to the use of price ranges provided by TripAdvisor instead market prices.

As mentioned previously, the prices used allowed us to focus on hotels' price strategies, regardless of their tactical level, which heavily depend on the volume of competitors in real time (Abrate & Viglia, 2016). According to Abrate et al. (2012), variations in prices react both to demand and competitors' actions that are generally the norm in the market. These trends are mainly associated with the segmentation of clients and hotel category.

Seasonal variations are particularly pronounced in the Spanish tourism sector (Guzman-Parra, Quintana-García, Benavides-Velasco, & Vila-Oblitas, 2015). Researchers have also confirmed that peak or off-peak season influences the prices of rooms offered in the tourism sector. Four models were thus developed for three reasons. Hedonic pricing models are sensitive to variations across time (Palmquist, 2005), two prices were available (i.e., minimum and maximum prices), and the study covered two cities. The models corresponded to the low and high seasons of each city. Table 2 provides an overview of all the variables and descriptive statistics for each model.

355 **Table 2**: Descriptive Values for Both Cities

Variable	Madrid		Barcelona	
	Min Price (n=362)	Max Price (n=359)	Min Price (n=417)	Max Price (n=418)
Price (£)	61.50	149.03	75.97	209.59
Establishment Variables				
Star	3.392	3.401	3.387	3.389
Number of Rooms	113.74	114.19	91.72	91.837
LnDistance	0.0362	0.0445	-0.2997	-0.298
Chain	39.50%	39.83%	27.82%	27.75%
Reputational Variable				
Overall Values	3.9023	3.9055	3.9946	3.9948
Certificate of Excellence	41.44%	41.78%	49.16%	49.04%
Photos	346.29	349.01	489.11	489.34
Neighborhoods				
City Center	58.56%	58.56%	69.06%	68.90%
Airport	3.87%	3.90%	–	–
Arguelles	1.66%	1.67%	–	–
Barrio de Salamanca	9.94%	10.03%	–	–
Centro	20.99%	20.61%	–	–
Chamberi	4.97%	5.01%	–	–
Chueca	4.42%	4.46%	–	–
Huertas	8.84%	8.91%	–	–
La Latina	1.66%	1.67%	–	–
Lavapies	0.55%	0.56%	–	–
Malasana	7.46%	7.24%	–	–
Paseo del Prado	3.04%	3.06%	–	–
Retiro	2.49%	2.51%	–	–
San Blas	3.31%	3.34%	–	–
Sol	10.50%	10.31%	–	–
Barceloneta	–	–	1.92%	1.91%
Barrio Gotico	–	–	13.67%	13.64%
Ciutadella-Vila Olimpica	–	–	2.16%	2.15%
Eixample	–	–	28.54%	28.47%
El Born-La Ribera	–	–	3.60%	3.59%
El Poble Sec	–	–	0.72%	0.72%
El Raval	–	–	15.83%	15.79%
Gracia	–	–	0.96%	0.96%
Horta-Guinardó	–	–	0.96%	0.96%
La Rambla	–	–	1.92%	1.91%
La Villa Olimpica de Poblenou	–	–	0.24%	0.24%
Les Corts	–	–	3.12%	3.11%
Montjuic	–	–	2.40%	2.39%
Pedralbes	–	–	0.72%	0.72%
Poblenou	–	–	2.88%	3.11%
Sant Antoni	–	–	2.40%	2.39%

Sant Pere	—	—	0.48%	0.48%
Style				
Best Value	14.36%	14.48%	15.35%	15.31%
Boutique	8.29%	8.36%	13.91%	13.88%
Budget	21.27%	20.61%	11.03%	11.00%
Business	59.12%	59.61%	65.95%	66.03%
Charming	24.31%	24.51%	38.13%	38.04%
Classic	22.93%	22.84%	23.26%	23.21%
Family-friendly	74.59%	75.21%	80.34%	80.38%
Green	5.80%	5.85%	7.67%	7.66%
Luxury	9.39%	9.47%	12.23%	12.20%
Mid-range	69.34%	69.92%	76.74%	76.79%
Quaint	1.10%	1.11%	1.44%	1.44%
Quiet	72.38%	72.70%	81.53%	81.58%
Romantic	12.43%	12.53%	21.10%	21.05%
Trendy	16.85%	16.99%	35.73%	35.65%
Amenities				
Air Conditioning	85.34%	85.52%	88.73%	88.76%
Airport Transportation	18.50%	18.38%	8.39%	8.37%
Bar Lounge	57.73%	57.38%	64.51%	64.59%
Beach	—	—	1.68%	1.91%
Breakfast Included	3.31%	3.34%	7.43%	7.42%
Business Services	46.41%	46.80%	47.72%	47.85%
Concierge	74.31%	74.37%	73.38%	73.44%
Fitness Center	26.80%	27.02%	29.98%	30.14%
Free Parking	1.38%	1.39%	0.96%	0.96%
Free Wi-Fi	93.92%	94.43%	90.65%	90.67%
Golf Course	—	—	0.24%	0.24%
Internet	97.51%	98.05%	99.28%	99.28%
Kitchenette	6.35%	6.41%	7.91%	7.89%
Meeting Room	55.25%	55.71%	57.79%	57.89%
Nonsmoking	46.13%	46.52%	56.35%	56.46%
Pets Allowed	14.92%	15.04%	15.83%	15.79%
Pool	12.71%	12.81%	32.13%	32.06%
Reduced Mobility Rooms	23.48%	23.68%	35.49%	35.41%
Restaurant	53.04%	53.20%	56.83%	56.94%
Room Service	60.50%	61.00%	60.91%	61.00%
Spa	5.52%	5.57%	9.59%	9.57%
Suites	43.37%	43.73%	47.72%	47.61%
Wheelchair Access	65.75%	66.30%	80.82%	80.86%

Source: Authors

3.2 Descriptive Analysis

The descriptive analysis highlighted several important points about the composition of the hotel sector in each city. First, prices are higher in Barcelona than in Madrid, which is

consistent with Soler et al.'s (2016) findings. Madrid has a slightly higher category of hotels than Barcelona, although the difference is miniscule. In addition, both the number of rooms per hotel and the number of hotels belonging to a chain are markedly higher in Madrid.

Moreover, Barcelona surpasses Madrid in all measures related to hotel reputation. The mean score of Barcelona hotels exceeds that of Madrid hotels by just under 10%. The same holds true for certificates of quality. Approximately 49% of Barcelona hotels have certificates compared with approximately 42% of Madrid hotels. The biggest difference, though, is in the number of hotel photos posted. Hotels in Barcelona post, on average, approximately 150 more photos per hotel than hotels in Madrid do.

Although neighborhoods in different cities cannot be directly compared, their degree of dependence on the city center can be compared for each city. The data indicate that Barcelona hotels are more highly concentrated in the city center than Madrid hotels are. This conclusion was reached by calculating, first, the proportion of hotels labeled as being in the center (58.56% in Madrid vs. 69% in Barcelona) and, second, the mean of the natural logarithm of hotels' distance from the city center. The mean was positive for Madrid and negative for Barcelona. The presence of a second location label referring to the city center of Madrid suggests that Madrid has one city center that can be more broadly defined and another that is more specific.

Significant differences also exist between the cities with regard to hotel styles. First, approximately 14% of Barcelona's establishments are labeled boutique hotels, whereas that figure is only 8% for Madrid. This finding can be explained by the smaller median size of Barcelona hotels. Second, the proportion of budget hotels is almost twice as high in Madrid as in Barcelona. In all other hotel styles, Barcelona surpasses Madrid, particularly in the categories of romantic and trendy hotels.

The hotels of these cities appear to be more evenly matched in terms of services and facilities offered, with a few notable differences. First, 18.5% of Madrid hotels offer airport transfers, whereas only 8.9% of Barcelona hotels offer this service. Second, the proportion of hotels offering breakfast included in the room price is almost twice as high in Barcelona as in Madrid. Third, approximately 32% of Barcelona hotels have a pool, whereas only 13% of Madrid hotels have one. Barcelona also has a higher proportion of rooms (35.49%) adapted for people with reduced mobility than Madrid does (23.68%). This difference is especially true for wheelchair access. A full 81% of Barcelona hotels have facilities adapted for guests with wheelchairs, but only 66% of Madrid hotels offer this feature.

In summary, both cities can clearly be described as tourist destinations, each with its distinct features that make them separate markets. Therefore, they needed to be analyzed with separate models, as was done in Soler et al.'s (2016) research.

4. Results

Table 3 displays the results for the four models. To control for multicollinearity, autocorrelation, and problems typically associated with hedonic pricing models, the variance inflation factors (VIFs) were calculated for multicollinearity, as suggested by Schamel (2012) and Soler et al. (2016), and for autocorrelation, based on the Durbin-Watson statistic. In all the models, autocorrelation can be discounted because this statistic falls within acceptable levels.

403 **Table 3**: Significant Parameters for

404 Madrid and Barcelona

	Madrid								Barcelona							
	Model 1				Model 2				Model 3				Model 4			
Variables	Beta		Standard Error	Standard Beta	Beta		Standard Error	Standard Beta	Beta		Standard Error	Standard Beta	Beta		Standard Error	Standard Beta
Interception	2.842	***	(0.162)		3.685	***	(0.275)		3.586	***	(0.341)		5.204	***	(0.403)	
Establishment Variables																
Star	0.080	***	(0.025)	0.179	0.113	***	(0.041)	0.204	0.118	***	(0.030)	0.244	0.192	***	(0.036)	0.392
LnDistance	-0.048	**	(0.019)	-0.136	-0.054	*	(0.031)	-0.124	-0.109	***	(0.037)	-0.198	-0.201	***	(0.044)	-0.362
Chain	0.090	***	(0.030)	0.108	0.021		(0.048)	0.021	0.031		(0.044)	0.028	-0.042		(0.051)	-0.038
Reputational Variable																
Overall Values	0.161	***	(0.036)	0.198	0.055		(0.058)	0.054	0.012		(0.061)	0.012	-0.175	**	(0.072)	-0.167
Certificate of Excellence	0.058	*	(0.034)	0.070	-0.092	*	(0.055)	-0.090	0.054		(0.044)	0.055	-0.031		(0.053)	-0.031
Photos	0.000		(0.000)	-0.027	0.000	**	(0.000)	0.124	0.000		(0.000)	0.041	0.000		(0.000)	0.091
Neighborhoods																
City Centre	0.043		(0.042)	0.052	0.182	***	(0.068)	0.177	-0.065		(0.056)	-0.061	-0.227	***	(0.066)	-0.213
Barrio de Salamanca	0.205	***	(0.049)	0.150	0.093		(0.079)	0.056		–					–	
Huertas	0.062		(0.047)	0.043	0.141	*	(0.076)	0.079		–					–	
La Latina	-0.208	*	(0.111)	-0.065	-0.045		(0.178)	-0.011		–					–	
Paseo del Prado	0.188	**	(0.080)	0.079	0.041		(0.128)	0.014		–					–	
Sol	-0.107	**	(0.049)	-0.080	-0.042		(0.081)	-0.026		–					–	
Horta-Guinardó		–					–		-0.196		(0.177)	-0.039	0.614	***	(0.210)	0.121
La Rambla		–					–		0.655	***	(0.142)	0.183	0.410	**	(0.168)	0.114
Les Corts		–					–		0.248	**	(0.109)	0.088	0.215	*	(0.129)	0.076
Sant Antoni		–					–		-0.216	*	(0.120)	-0.067	0.211		(0.142)	0.065
Style																
Best Value	-0.074	*	(0.043)	-0.064	-0.078		(0.069)	-0.054	0.003		(0.054)	0.002	-0.068		(0.064)	-0.050
Budget		–					–		-0.407	***	(0.109)	-0.260	-0.161		(0.129)	-0.102

Charming	0.082	*	(0.044)	0.086	0.086		(0.071)	0.073	0.076		(0.057)	0.075	0.017		(0.068)	0.017
Classic	0.068	*	(0.037)	0.070	0.032		(0.060)	0.027	0.079		(0.049)	0.068	0.048		(0.058)	0.041
Family-Friendly	-0.030		(0.036)	-0.032	-0.018		(0.058)	-0.015	-0.096	*	(0.055)	-0.078	-0.075		(0.065)	-0.060
Luxury	0.579	***	(0.083)	0.412	0.542	***	(0.134)	0.314		–					–	
Mid-Range	0.237	***	(0.044)	0.267	0.278	***	(0.071)	0.252	-0.379	***	(0.074)	-0.326	-0.226	***	(0.087)	-0.193
Quiet	-0.033		(0.036)	-0.036	-0.080		(0.057)	-0.070	-0.128	**	(0.055)	-0.101	0.070		(0.065)	0.055
Romantic	0.150	**	(0.061)	0.121	-0.036		(0.098)	-0.024	0.157	**	(0.068)	0.131	0.191	**	(0.081)	0.157
Amenities																
Airport Transportation	-0.047		(0.038)	-0.044	0.024		(0.061)	0.018	0.139	*	(0.071)	0.078	0.047		(0.084)	0.026
Breakfast Included	0.010		(0.073)	0.004	0.135		(0.117)	0.048	0.071		(0.070)	0.038	-0.153	*	(0.083)	-0.081
Internet	-0.138		(0.108)	-0.052	-0.034		(0.191)	-0.009	0.357	*	(0.209)	0.061	0.180		(0.247)	0.031
Non-smoking	-0.057	*	(0.030)	-0.070	0.011		(0.048)	0.011	0.021		(0.038)	0.021	-0.051		(0.045)	-0.051
Pets Allowed	0.021		(0.037)	0.018	0.050		(0.059)	0.035	-0.034		(0.048)	-0.025	-0.123	**	(0.056)	-0.091
Pool	0.052		(0.043)	0.042	-0.026		(0.070)	-0.017	-0.095	**	(0.048)	-0.090	0.004		(0.056)	0.004
Restaurant	-0.049		(0.037)	-0.059	0.110	*	(0.060)	0.109	-0.031		(0.050)	-0.031	0.040		(0.059)	0.040
d	1.837			1.909					1.960						1.737	
$\bar{R}^2$	0.695			0.483					0.555						0.386	
F	15.703***			6.976***					9.513***						5.294***	
MdAPE	2.92%			3.35%					3.34%						3.30%	

Note: *Statistical significance at the 95% level; **statistical significance at the 99% level; ***statistical significance at the 99.9% level; d = Durbin-Watson coefficient; = corrected coefficient of determination; F = F-value; MdAPE = median absolute percentage error

Source: Authors

With regard to multicollinearity, all VIF values are below the critical values suggested by Kennedy (2008), with the exception of the "budget" variable in Madrid and the "luxury" variable in Barcelona. When multicollinearity exists, normally the number of variables can be reduced, or they can be grouped together (Aguiló et al., 2003; Andersson, 2010). In the present study, the two variables could be eliminated without compromising the content validity. Once these variables were excluded, none of the models showed significant multicollinearity, fulfilling all the requirements for their continued use.

The model fit is better for Madrid than for Barcelona, and the fit is also better for the low season than for the high season. In all four models, hotel category has a significant positive impact on room prices. Distance from the city center has a significant negative impact on prices in all models. Regarding hotel style, only the "mid-range" position is significant in all models. The hotels' city-center location is significant in both cities during the high season, although the sign is different for each city. The other significant values vary depending on the city or season. These results are discussed in the following section.

5. Discussion

This research's approach included some innovations that took greater advantage of the data, which, until now, have not been considered in studies with hedonic price models. First, the range of prices provided by TripAdvisor was used as a proxy of high- and low-season prices, combining the advantages of catalog prices with market prices. This provided a more strategic model of how hotel prices are constructed that eliminated the effects of events held on specific dates. Second, this is the first study to start a discussion about—and consider the possibility of—using the adjustment capacity of the proposed research model as another source of information on the importance of external variables. These, in their broadest sense, are linked to destinations through the configuration of hotel room prices.

Based on the results described above, the model fit can be said to be better for Madrid than for Barcelona. The reason for this difference is that the amenities offered by hotels alone cannot explain hotels' pricing policies at a strategy level. Therefore, this specific result is more clearly due to external factors. These include, among others, city services, the growing power of the alternative lodging industry, successful brand management by these destinations' DMOs, and the use of prices as a tool when reacting to concrete situations at specific times (e.g., prices as a tactical tool). These unobservable factors could be behind the present counterintuitive results for the formation of prices. The current findings can thus be explained from a rational perspective through a focus on maximizing the functions of supply and demand (Benítez-Aurioles, 2018).

González-Rodríguez, Jiménez-Caballero, Martín-Samper, Köseoglu, and Okumus (2018) suggest that hotel managers are trying to increase both occupancy rates and sales through revenue management, as managers are aware of the significant influence these variables have on hotels' profitability. This effect implies the need for extensive price variations to compensate for the equally wide variations in demand, as well as improved performance through technological differentiation in distribution channels. The latter is closely linked to price fluctuations, making it difficult to position hotel services clearly in the market.

Therefore, hotels and their services are more dependent on external factors affected by time. In other words, hotels are positioned in the market by pricing policies that react to demand and that are more aligned with market prices and panel data, such as those used by Abrate and Viglia (2016), than with proactive pricing strategies based on catalog prices. Overall, hotel pricing in Barcelona relies more heavily on the city's specific conditions and its DMOs' ability to manage and promote the city's brand, as well as taking full advantage of the tourist resources available in this city.

Logically, these services are neither homogenously distributed nor equally valued throughout cities. Furthermore, the destination brand image fostered by DMOs may or may not favor certain hotels. This spatial heterogeneity could mean that certain hotels operate in suboptimal areas in terms of external resources, which condition their pricing policies. This heterogeneity and its impact on prices and ability to alter patterns of quality-value perceptions in cities have already been confirmed for other Spanish cities, such as Malaga (Soler & Gemar, 2018). This previous finding can reasonably be extrapolated to Madrid and Barcelona since both are larger than Malaga. In these two cities, the weight of destination factors could eclipse individual hotels' attributes and their capacity for differentiation.

Notably, although Barcelona may be successful at attracting more tourists and thus improving hotel occupancy rates, the lack of correlation between this city's hotel amenities and hotel room prices could lead to a proliferation of an alternative lodging industry. This could replace hotel rooms with such offers as tourist apartments, vacation rentals, and residents who illegally rent out their homes to tourists. This is in line with the proliferation of other forms of tourism, including the collaborative economy—with Airbnb as its standard bearer.

Airbnb has put in jeopardy the revenues and survival of several types of lodging, including some hotels (Guttentag & Smith, 2017). Prices are one of the most important motivators in consumers' use of Airbnb, which has produced disruptive changes throughout the tourism industry (So, Oh, & Min, 2018). Blal, Singal, and Templin (2018) have found proof that customers make dynamic comparisons between the prices and value provided by both conventional hotels and Airbnb. This trend could be aligned with the results of the present study, which indicate a loss in the differential value of hotel services, as measured by clients' willingness to pay for the implicit attributes of these services, especially in peak season and in Barcelona.

Gunter (2018) suggests, based on research in San Francisco and the Bay Area, that hoteliers should adapt their offer and put more emphasis on communicating their advantages to customers if they want to remain competitive in the accommodation market. Hotel managers need to compensate "partially" for their higher prices and lack of perceived authenticity in comparison with Airbnb. In the same vein, Akbar and Tracogna (2018) argue that hotels have to develop "integrated platforms" that allow these companies to communicate their advantages by categorizing them according to three key features: frequency, uncertainty, and asset specificity. In other words, hoteliers should improve their digital marketing strategy to strengthen their hotels' performance (De Pelsmacker, van Tilburg, & Holthof, 2018).

Various researchers such as Zervas, Proserpio, and Byers (2014) have confirmed a negative relationship between an increase in Airbnb listings and a decrease in quarterly hotel revenues. Blal et al. (2018, p. 90) report that "hotel managers can no longer ignore the Airbnb offer in their destination as the platform offer is not a mere supplement of lodging product." This website's popularity has continued to grow, especially since 2008, thanks to its low prices and direct interaction between tourists and homeowners who rent houses or rooms for short periods of time (Zhang, Chen, Han, & Yang, 2017).

Spain currently is ranked on Airbnb as the country with the fourth highest number of listings (Abdar & Yen, 2017). These alternative accommodations can consider the same external factors as hotels when setting their prices without having to offer hotel services and with a much different cost structure. This could create a unique situation in which hotels may be endangered by Barcelona's popularity. This destination's success and the resulting resources increase the level of local competition, especially for those businesses with low barriers to entry. Competition in a market with no barriers to entry implies the absence of profits in the long run (Rosen, 1974), which could explain hoteliers' demand for more control

of these alternative accommodations. This context implies a moderating effect on the differentiation of prices, which is in agreement with Becerra et al.'s (2013) results. The present finding is also in line with Singh's (2008) suggestion that a large number of tourists can be counterproductive for hotels.

These results also indicate that hedonic pricing models must be adapted to fit the particular destinations under study. Destinations' assets play a crucial role in shaping travelers' preferences, and, thus, the literature on hedonic pricing must build on the particularities of each destination when making generalizations. This also implies that each destination must be examined individually to understand more fully customers' willingness to pay for different destinations' attributes, so DMOs' cannot directly extrapolate from the results of studies of other destinations.

In the present research, all the models showed a significant positive correlation with hotel category, a significant negative correlation with hotels' distance from the city center, and no correlation with hotel size, which is in line with the existing literature on hedonic pricing. The results confirm that, in both Madrid and Barcelona, guests view hotel category as a good indicator of hotels' quality. This confirms that the hotel classification system is a good forecaster of hotel prices (Martin-Fuentes, Fernandez, Mateu, & Marine-Roig, 2018), although this variable is more important for hotels in Barcelona than for those in Madrid.

However, the current comparison of the standard low-season prices for Madrid showed that user ratings on TripAdvisor have a greater impact than hotel category does, which is in line with the findings of some authors. For example, Abrate and Viglia (2016) and Torres, Adler, and Behnke (2014) report that hotels' online reputations are beginning to replace hotel category as the most reliable measure of their quality. Given that the official system of star categories is not homogenous around the world (Martin-Fuentes et al., 2018), hotel category may only influence clients' willingness to pay when this information is

reinforced by other indicators of quality, as de la Peña et al. (2016) suggest. However, in the present study, the greater importance of online reputation as an indicator is restricted to the specific case of Madrid during the low season, while hotel category remains, overall, a significant, stable indicator of hotels' quality.

Another aspect of the results worth noting is how variables' significance varies by season and how they lose their explanatory power for both cities in the high season. This finding could be explained by the increasing importance of factors external to hotels during the high season. During this season, destination-related factors such as better weather and a proliferation of events logically become more important than factors related to the hotels themselves. This may explain the high-season proliferation of the aforementioned secondary industry of alternative accommodations, which operate with a smaller investment and lower-cost structure than hotels do. These alternatives absorb some of the profit produced by destinations' ability to attract paying customers and disappear when the high-season demand wanes. The entry and exit of potential competitors could diminish the predictive power of the proposed models and variations in significant variables.

These findings again show the importance of the time factor in hedonic pricing models and confirm that the high season raises prices and alters clients' spending patterns. Therefore, these results must also be addressed on a methodological level. Hedonic pricing studies need to develop separate models based on tourism seasons within cities and avoid including dichotomous variables to separate these seasons. If dichotomous variables are included, then evidence should be provided that the variables' specific weight does not vary across the different periods in question.

When the data on hotels were decomposed by city, seasonal variations were detectable in the pricing patterns. For example, in Madrid, the importance of neighborhoods varies by season. In the low season, central locations' effect is not significant, other

neighborhoods such as Salamanca and Paseo del Prado have a positive impact, and some neighborhoods such as Latina or Sol have a negative effect. However, these variations change in the high season, when the city center's influence becomes significant, positive, and greater in terms of standardized measures than any other neighborhood. Hotels' location in the Huertas neighborhood is also significant and positive during the high season.

In Barcelona, some locations, such as the neighborhoods of Las Ramblas and Les Corts, have a significant positive impact in both seasons. The importance of other locations varies, depending on the season. Sant Antoni's effect, for example, is significant and negative in the low season, and the neighborhood of Horta-Guinardó has a significant positive impact in the high season. Perhaps the most peculiar result is that customers' willingness to pay for hotels located in the center of Barcelona has a significant negative effect in high season. This may be due to the existence of negative factors in this neighborhood during the high season, such as crowds and nightlife noise, which could cause visitors to avoid spending the night in this area but value a nearby location.

The results show that few amenities and services offered by hotels are significant, and none have effects that persist across different cities and seasons. This is further proof of the reduced power of differentiation for hotels offering their own services and facilities. Zhang, Jahromi, and Kizildag (2018) suggest that guests might neither sufficiently experience the utilitarian benefits of hotel features nor make the most of products' association with social class, social status, or specific social groups. Some labels with negative signs may even be counterproductive to hotels' differentiation strategies, such as the non-smoking label for Madrid hotels in the off-peak season. This may be because these services are associated with lower-level hotels or because those who seek to differentiate themselves with these labels do so because they lack other better means of differentiation.

Hotel prices in these destinations could be largely determined by destination assets, hotels' location strategies, and key attributes that potential consumers use as quality markers (e.g., hotel category and brand image). Therefore, hotels need to change their approach to operating in the current environment in order to improve customers' experiences and satisfaction levels (Soler & Gémar, 2017a). These findings support the conclusion that indicators of the perceived quality of hotels' amenities and services may have more of an impact on prices than the amenities and services themselves do, which was also confirmed by Matzler, Renzl, and Rothenberger's (2006) research.

Soler et al. (2016) applied this approach in their study of Madrid and Barcelona hotels, using perception and fewer variables rather than physical attributes. In contrast to the cited authors' results, the present study suggests that the importance of online ratings vary by season, as well as by city. This may be due to changes in the format of the TripAdvisor rating system and the current research's use of TripAdvisor's price range instead of market prices.

In addition, Soler et al. (2016) achieved model fits that were slightly inferior to the present study but similar for both cities. The cited authors also showed that hotels' membership in a chain is significant for Madrid but not for Barcelona, which the present study corroborated. Another difference is that the present study found that hotels' characterization as "green" has no significant impact in either city, whereas Soler et al.'s (2016) results show that this characterization is significant in Barcelona.

The present study included a greater number of labels indicating hotel style. In both cities, significant correlations were found between hotels' style labels and their pricing policies, except for Barcelona hotels labeled "budget" during the high season. This finding may appear obvious, but the most interesting aspect of how hotels position themselves in the market is the seasonal variations in customers' willingness to pay for these labels. For example, Madrid hotels' efforts to label themselves as charming, classic, and romantic show

a significant and positive correlation with pricing in the low season but not in the high season. These findings show a patterned change with respect to the season and the existence of different sub-destinations within the same destination, depending on the time period under study. Nonetheless, in Barcelona, being a romantic hotel has a significant positive impact on pricing in both seasons, possibly due to the positioning of the destination itself.

Finally, the effect of having the label "quiet" is significant and negative in the low season, and insignificant in the high season. Perhaps quiet hotels are associated with areas of little interest or being "quiet" is not valued. In addition, a serious problem may exist in Barcelona with regard to the negative visible consequences of tourism. Notably, approximately 81.5% of Barcelona hotels claim to be "quiet."

6. Conclusion

This study sought to measure and compare the extent to which hotel prices in Madrid and Barcelona are dependent on the attributes of their respective destinations. The research used an innovative approach by applying hedonic pricing models to measure this dependency based on price, making a simultaneous comparison of both cities' hotels possible. This approach also facilitated a comparison of the results with other hedonic price studies because of the similarity of the present models' functional form to that of the models generally applied in research on other destinations. The findings have both practical and methodological implications.

Regarding methodological implications, previous studies have, hitherto, mainly focused on ensuring models run smoothly, forgetting that the adjusted coefficient of determination measures the percentage of variation in the price variable, depending on the variables used. This means that the variation that remains unexplained can be used, and it needs to be discussed to exploit these models' full potential. In addition, this study is the first to propose the use of the range of prices provided by TripAdvisor as a proxy for low- and

high-season prices. This offers advantages by combining the advantages of catalog prices with market prices, thereby facilitating an exploration of the strategic components of hotel prices in specific destinations.

Another methodological implication is the need to remember this type of model's sensitivity to time. The present results show that the high season not only brings higher prices but also changes the patterns of significance for both cities. Thus, hedonic pricing models should develop different models for each season within a single city. If dichotomous variables are included to separate seasons, then evidence needs to be shown that these variables' specific weight does not vary across different periods. This finding can be extended to include separate models for weekday and weekend pricing.

In terms of practical implications, the results show that Barcelona's hotel prices are more dependent on external factors such as destination attributes, which could indicate successful management by DMOs. These attributes and the timeframe should have more of an impact than hotels' strategic positioning of room prices since final prices are largely a product of hotels' adaptation to demand and their competition's actions. The MdAPE obtained at least partially validates these results (see Table 3 above). This greater dependency means that hotels can charge a higher room rate because of resources external to these establishments. However, because the resources do not belong to the hotels, anyone can absorb part of the profit derived from these destination attributes. Future research is needed to deepen the existing understanding of dependency factors, their causes, and possible patterns associated with them.

This greater dependency on external factors thus has as its counterpart less influence and control over prices by hoteliers, which can explain the proliferation of competing platforms such as Airbnb. Greater dependence on such resources means a greater propensity for potential alternative competitors to enter the market and a greater exposure to variations

in the destination environment. The more hotels depend on the surrounding destination, the more they tend to press for limitations on new competitors of all kinds and higher barriers for those seeking to enter the market. More in-depth information is needed about how Airbnb and other accommodation formats affect the formation of hotel room prices, so we would encourage more research along these lines.

The study also shows that hotels in both cities become more dependent on their destination during the high season. This finding could explain the high-season proliferation of the types of lodging that operate with a smaller investment and lower cost structure, which absorb some of the profit generated by destinations' ability to attract paying guests. These alternative accommodations disappear when the demand wanes. In addition, the models applied reveal which hotel amenities' have an impact on prices in both cities, which may be useful to hotel managers in guiding their operations toward features for which guests are willing to pay more.

This study has some limitations that need to be mentioned. First, the full range of TripAdvisor information was collected and, thus, the most important and repeated internal variables of the literature could be included. The remaining data were associated with external or destination variables. This sampling method, however, may have left some internal variables unaccounted for, such as hotel age (Hung et al., 2010), when these did not appear on the TripAdvisor website. Nonetheless, any missing internal variables can be considered insignificant because of the importance given to external variables in the model.

Second, this research compared only two cities, which were treated as unique and undifferentiated markets due to the nature of the hedonic price model, and the hotels in each city were included without considering their distinct offers to specific consumer profiles, namely, without market segmentation. For example, the impact of amenities on hotel rates could differ between luxury and budget hotels or between city-center and airport hotels.

Heterogeneity and spatial autocorrelation need to be taken into account in future research using hedonic price models given these aspects' impact on the determination of different prices throughout each city (Soler & Gémar, 2018; Zhang et al., 2011).

More cities could have been included, but this would have compromised the comparison of results due to significant differences such as city size and country-level macroeconomic conditions. A third limitation is the sample size, which is smaller than the samples used in other hedonic pricing studies. This was made necessary by the study's objectives. To maximize the number of cases, the largest Spanish cities were chosen. If a greater variety of data were collected for each hotel, the number of cases in the regressions could have been increased by combining these data with specific dates. However, doing this would have tied the data to dates, which would mean destination-specific and date-specific conditions such as events and weather conditions would have interfered with the results found. In addition, other time-related conditions would have to be taken into account, such as the date of reservations and the booking margin, which were considered destination components for the purposes of this study.

A fourth possible limitation is that all the data and, thus, the results are associated with a single source: TripAdvisor. Although this website is the world's largest travel community, results based on data gathered from other websites could be different. Last, market data and hedonic pricing models are notably sensitive to variations, so future changes in the selected destinations or hotels' attributes might significantly change levels of dependence.

Future lines of investigation need to increase their used of destination-specific data and their findings' contributions to the success of hotel businesses. This study barely scratched the surface in this respect, so more research must be done along these lines. Further studies could extrapolate the present procedure to other cities to determine the degree of

hotels' dependency on the surrounding destination. Interesting results may also be obtained by applying the proposed model to another type of accommodation and even comparing this with hotels to check whether the level of dependence differs. Doing so, however, would be a difficult task due to the challenge of collecting the same variables for both forms of accommodations, which, if done improperly, could result in different and incomparable models.

In addition, an analysis should be carried out of differentials between high- and low-season prices using as a proxy the mean prices calculated by TripAdvisor. This could lead to valuable findings on the strategic components behind prices in different destinations. Moreover, researchers may achieve worthwhile results by comparing hedonic prices provided by websites, thereby producing more interesting findings by measuring the explanatory power of prices, maintaining a focus on destinations, and collecting data from a variety of websites. Finally, future studies could achieve significant results by comparing the relationship between hotel managers and DMOs in scenarios in which hotels are more dependent or less dependent on destination attributes.

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