Modeling hotel room pricing: A multi-country analysis

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Abstract

In the current tourism landscape, pricing decisions reemerge as a key concern for hoteliers. This study examines the impact of specific factors associated with hotels, customers' experience, and competition on hotel pricing in different countries. Certain features of market behavior can distort expected prices, such as asymmetric information, differences in hotel categorization, hotels spatial concentration or electronic word-of-mouth (eWOM). In order to understand the determinants of pricing and to obtain a complete characterization of them, the present study applies quantile regression to the prices of a sample of 3,800 hotels located in France, Spain, Italy and the United Kingdom. Results show the heterogeneity of the effects of hotel category, country location, eWOM and hotel competitive intensity across different price levels. Also, hotels concentration proves to have a generally positive effect on price, confirming positive effects of spatial concentration.

Keywords:

Hotels; Pricing; Spatial concentration; Category; eWOM; Quantile regression; Multi-country; Europe

1. **Introduction**

The objective of this study is to deepen the understanding of hotel pricing decisions by analyzing heterogeneous effects of hotel's characteristics, customers' experience, competition and country on fixed prices. A quantile regression model is used based on hotels from four countries.

The present work can be justified by several reasons. Firstly, at a conceptual level, the widespread use of dynamic pricing strategies (Abrate and Viglia, 2016) produces incentives to understand the price tactics of every hotel on an individual basis, increasing traditional properties of flexibility and utility of price in marketing programs, such as promotions (Abrate et al., 2012; Tanford et al., 2012), yield management (Emeksizet al., 2006), lodging choice (Kim and Park, 2017), or customer satisfaction (Radojevic et al., 2015). Additionally, the vast development of multichannel strategies in hotels has led to the implementation of price changes more quickly than in conventional environments, requiring more intense and frequent management (Beritelli and Schegg, 2016; Toh et al., 2011).

Second, hotel pricing models incorporate category as an apparent unbiased signal of services selection and establishment quality based on regional regulations (Becerra et al., 2013). Although it offers the advantage of summarizing into an indicator an entire set of specific attributes (Azzopardi and Nash, 2013), several issues question category as an unbiased predictor. For example, hotel chains display problems associated with specific asymmetric information (Akerlof, 1970) and tourists have limited information about future prices and room availability (Chen and Schwartz, 2006). It has been verified that ranking by quality may not correspond to categories (López-Fernández and Serrano-Bedia, 2004). In particular, different regional and national regulations for hotel categorization are a source of heterogeneity that deteriorates its value as a standard quality signal (Nuñez-Serrano et al., 2014). What is more, many hotels draw on additional strategies to communicate their quality and service levels (Nicolau and Sellers, 2010). To understand the behavior of the category as a determinant signal of room price, we intend to evaluate its effect for different price levels and different countries.

Third, further hedonic modeling, pricing competition has basically been addressed from a differentiation perspective, yielding a negative main effect, but one which is not conclusive because it is conditioned to the type of moderator used (Becerra et al., 2013). However, evidence of divergence does exist. On the one hand, some hotels follow a price parity strategy to attract customers (Toh et al., 2011), avoiding a race to the bottom in room price. Also, from the spatial concentration perspective, the derived effect from competition can be positive. More specifically, the Central Place Theory (CPT) (King, 1984) postulates the existence of a concentration effect since economic activities are prone to cluster together in specific market areas. As a consequence, Daniels (2007) describes the relationship between the size of the available tourist activities in one place and the economic impact on each. However, spatial concentration effect on the price set by hotels has not been tested.

Fourth, the widespread use of social networks in C2C and B2C fields through comments and online rankings has shown its efficacy for explaining pricing (Yadav and Pavlou, 2014). From a demand perspective, the generalization of price information availability on the Internet has increased knowledge about hotel prices and, therefore, changed customers' evaluations (Noone and Mattila, 2009). Particular attention has been placed on the impact of eWOM (Cantallops and Silva, 2014), confirming customers' independence when they make reviews and its relevance as an information source (Yan and Tang, 2019). However, the relationship between eWOM and price has been recently considered in price modeling. Thereby they may provide misleading notions of the influence of clients' experience (Tsao et al., 2015). It has been incorporated into hedonic price models (HPM) as a room rating (Zhang et al., 2011b), as hotel online ratings (Ivanov and Piddubna, 2016), or as a hotel reputational measure (Abrate and Viglia, 2016).

Finally, regarding the generalization of results, hotel pricing research has focused on selection available in a city (Abrate and Viglia, 2016; Pawlicz and Napierala, 2017), type of city (Abrate et al., 2012; Baldassin et al., 2017), or a particular country (Becerra et al., 2013). However, tourism environments and markets differ across cities and countries, ultimately influencing management decisions and strategies. In fact, the sequence of the implementation of standards in the hotel industry also vary depending on the country (Zeng et al., 2007), and there are differences in hotel management related to property management, offer and hotel category (Pine and Phillips, 2005). This factor should be considered to avoid results that may distort real patterns.

These factors, apart from adding relevance to research on pricing, increase the use of price in hotel marketing decisions, which in turn causes a predictable increase in price variability. These results contradict the evidence that price instability has a negative effect on hotel profitability, i.e. Tisdell's model (Chen and Chang, 2012).

Tourism decision-making process requires considering different variables from decision areas that interact simultaneously and make it possible to adequately understand variations between prices offered by hotels (Abrate and Viglia, 2016). However, effects on hotel price vary across different price levels (Hung et al., 2010; Masiero et al., 2015). Therefore, hotels attributes and tourist experiences, coupled with country differences and competences, require flexible models which adequately describe heterogeneity for hotel level pricing practices. Quantile regression is applied to contrast whether the effects of the independent variables over hotel price are not constant; its use is especially recommendable for asymmetric variables and distributions with long tails (Koenker and Bassett, 1978), where the ordinary least squares (OLS) method may result in erroneous estimates.

Therefore, our study aims to provide several contributions. Firstly, since hotel price variations require considering different decision areas that interact simultaneously (Abrate and Viglia, 2016), determinants are combined from perspectives of customer, hotel, competition and hotel country, thereby enhancing partial models. Secondly, the effect of hotel category is evaluated for different price levels and countries. Thirdly, from the assumptions of CPT, evidence is provided of the competitive effects of spatial concentration on price. Fourthly, our work seeks to fulfill the need to expand studies on the effect of eWOM on pricing decisions (Cantallops and Silva, 2014). Finally, with the purpose of providing a general approach to hotel pricing studies, our work applies quantile regression, allowing non-constant effects of the determinants, and with a large sample data set (3,800 hotels) from different cities in four EU countries with substantial tourist activity.

2. Literature review

2.1. *Hotel room pricing models*

Hedonic models (Rosen, 1974) have been the most widely-used approach to explain hotel prices. Anyway, models of competition (Becerra et al., 2013) or monopolistic models based on cost (Van Dijk and Van der Stelt-Steele, 1993) have also been considered. Basic contribution of HPMs is to provide evidences on the importance of each hotel attribute for income generation, mostly through regression analysis (Masiero et al., 2015). Results obtained have confirmed the effect of both age and restaurant availability (Bull, 1994), category (Becerra et al., 2013; Israeli, 2002), type of location (Espinet et al., 2003), chain affiliation (Becerra et al., 2013; Israeli, 2002), parking availability (Espinet et al., 2003), hotel size (Zhang et al., 2011a), room size or spa availability (Abrate and Viglia, 2016), hotel facilities and technological resources available (Chen and Rothschild, 2010), staff size (Hung et al., 2010; Chen and Chiu, 2014) and customer evaluation of service quality (Zhang et al., 2011b) (see review in Table 1).

The extension of pure HPMs has been developed by incorporating new attributes based on the customers themselves (Thrane, 2007), such as user-perceived quality (Chen and Chiu, 2014), advanced booking effects (Abrate et al., 2012) or the different types of eWOM (Abrate and Viglia, 2016; Pawlicz and Napierala, 2017; Zhang et al., 2011b). Other approaches, such as differentiation or competition effects, have been marginal (Becerra et al., 2013), and, moreover, the application of models that allow non-constant effects on price has been even less frequent. Only Hung et al. (2010) have applied HPM based on quantile regression from a supply perspective, while Masiero et al. (2015) have also applied this model from the demand side.

From a methodological point of view, some of the common features utilized in previous studies include the exploration of the lodging industry in specific locations and the generalized use of the OLS method, which assumes constant effect of pricing determinants. The OLS method requires initial assumptions and non-fulfillment may result in less efficient estimates. Indeed if the conditional distribution of the dependent variable is asymmetric, the assumption of normal error terms is not guaranteed, implying a risk of undesirable estimations. Other methodological alternatives, when the non-fulfillment of OLS assumptions occurs, include geographically weighted regression (Zhang et al., 2011a) and a time series related estimation method (Lee, 2011).

In relation to the generalization of management implications, most studies have focused on hotels from a specific geographic area (city or country). Abrate et al. (2012) propose an HPM based on data from eight European capital cities, focusing on the analysis of pricing strategies. Baldassin et al. (2017) study determinants of prices in twenty six European cities with a two-step estimation procedure, finding differences in terms of cost and quality.

Research setting	Analitical model	Dependent variables	External factors	Internal factors	Researchers
One location (city, town..)	Linear, quadratic, semilog and loglinear hedonic analysis	Room rate	Location	Ranking stars, age, restaurant	Bull (1994)
	Linear hedonic analysis, Semilog hedonic analysis or loglinear hedonic analysis	Room rate	Location	Chain, beds, amenities	Thrane (2007)
				Ranking stars , chain, room size, amenities	Chen and Rothschild (2010)
				Ranking stars , chain, number of rooms	Pawlicz and Napierala (2017)
			Online reviews, booking time, weekend, competence	Ranking stars , number of rooms, , average occupancy, free cancellation, amenities	Abrate and Viglia (2016)
		Average room rate	Location	Category, cleanliness, number of rooms, amenities	Zhang et al. 2011a)
				Category stars, number of rooms, year	Zhang et al. (2011b)
	Multiple equation model	Peak season price and off-peak price	Location	Ranking stars, number services, number rooms, brand, presence guidebook, quality certification, amenities	Abrate et al. (2011)
	Linear, quadratic, semilog and loglinear hedonic analysis	Room rate	Location	Chain, AAA rate, amenities	Wu (1999)
One country (different cities, towns,..)	Linear, quadratic, semilog and loglinear hedonic analysis Random-effect hedonic price model, SEM, latent growth curve models	Room rate Average monthly daily room rate	Location Temperature, interstate location, and specialization of the local economy	Ranking stars, brand	Israeli (2002))
				Ranking stars, establishment variables, hotel style, amenities, contextual Attributes	Soler et al. (2019)
				Amenities	White and Mulligan (2002)
			Town,location	Ranking stars , establishment variables, amenities	Espinet et al. (2003)
			Geographical distance, number competitors	Ranking stars, room discount, size, age, chain, type of hotel	Becerra et al. (2013)
			Real gross domestic product , exchange, visitor arrivals, consumer price index, location	Occupancy, chain, service quality, room size, amenities	Chen and Chiu (2014)
		Average room rate	Market condition, location	Establishment variables, chain, resort, foreign travellers, housekeeping staff per room	Hung et al. (2010)
		Monthly room price	Town, climate	Ranking stars , establishment variables, amenities	Coenders et al. (2003)
	Time series (GARCH)	Room rate	Total tourist arrivals, terrorist attacks, industrial production	Not applicable	Lee (2011)
Different countries and different cities	Linear, quadratic, semilog and loglinear hedonic analysis	Room rate	Score, location, environment, booking day and time effects	Ranking stars, size, brand, cancelation, star rating, booking day, city as dummy available services	Abrate et al. (2012) Baldassin et al. (2017)

Table 1. Empirical models of hotel room price in selected publications

2.2 Hotel ranking stars

Star category is one of the most commonly used variables in hotel pricing models (Table 1) and verifies its positive effect on price (Bull, 1994 and Israeli, 2002). This is the indicator of services and quality offered by hotels (Pawlicz and Napiella, 2017). It has traditionally been considered the key explanatory variable of room price (Bull, 1994, Israeli, 2002), even the most influential (Espinet et al., 2002, Zhang et al., 2011), showing a highly consistent effect for different channels (Tso and Law, 2005). In addition, a high category is usually associated with greater affiliation to quality programs and better physical attributes (Abrate et al., 2011). Even hotel category is an influential factor in dynamic pricing strategies because high category allows maintaining stable prices when the general price trend is decreasing and also allows a more pronounced increase when the trend is rising (Abrate et al., 2012). Likewise, hotel category makes it possible to reduce negative effects of competitive rivalry on prices (Becerra et al., 2013).

These studies implicitly make assumptions based on Signaling Theory (Spence, 1973) since potential customers utilize hotel category as a signal to choose desired accommodation to fit their preferences, inducing to a positive relationship between category on price. However, hotels has traditionally been considered as an example of information asymmetries, questioning category as a signal for the consumer and requiring counteracting mechanisms (Akerlof, 1970). Furthermore, Signaling Theory conditions may not always be fulfilled. Thus, the assumption of pay off transparency constitutes an important criticism against signaling models (Kirmani and Rao, 2000), mainly because tourists have much less information about future prices and availability than service providers (Chen and Schwartz, 2006). Similarly, as for one-time tourists with limited access to word-of-mouth, relying on repeated bookings may not be suitable (Wolinsky, 1983).

It has also been found that ranking by quality does not correspond to ranking by categories (López-Fernández and Serrano-Bedia, 2004). Though official star classification is considered a good quality indicator, there is also significant quality overlapping between adjacent official categories. More specifically, different local and national regulations for hotel categorization are a source of heterogeneity that deteriorates its value as a standard quality signal (Nuñez-Serrano et al., 2014). Further, Nicolau and Sellers (2010) consider that hotels seek additional signals other than category from third parties to communicate their quality.

2.3. Hotels competence

Evidence on competition effects on hotel price indicates that room price increases when room availability among direct competitors decreases (Abrate et al., 2012). From the Industrial Organization perspective, Becerra et al. (2013) find a negative relationship between hotel concentration and hotel prices. However, they use vertical differentiation strategies based on category, finding that competition interacts with category, which reduce the negative effect of competitive rivalry on prices.

In contrast, the CPT (King, 1984) posits a positive relationship between the size of the selection of tourist activities available in a place and the economic impact on each one (Daniels, 2007), based on the logic that hotels tend to be located close to each other to increase supply, improve efficiency and survive (Barros, 2005, Yang et al., 2012). By applying this view, the positive relationship between agglomeration degree and hotel's benefit has been supported (Chung and Kalnins, 2001, Canina and Harrison, 2005). Furthermore, given that the existence of hotels in an area may increase the attractiveness of the location, nor the type of hotel establishments located in a certain location, nor the intensity of their agglomeration will necessarily be the same for all price levels, being useful to know the effects of competition for different price levels.

In contrast, approaches to competence based on aggregation posit a positive relationship between the size of the selection of tourist activities available in a place and the economic impact on each one. Specifically, CPT (King, 1984) describes patterns of business location in cities, so that larger urban places would have the larger offer of services. The theory assumes that both individuals and businesses are rational. Also, it is assumed that a "service would not be produced and sold if a profit could not be realized" (King, 1984, 30). Further, market areas are determined by the range between the minimum demand to break even and the maximum distance a customer would travel to obtain the service (Daniels, 2007). Every market –i.e., central place, is characterized by a specific offer and economies (Derudder and Witlox, 2004). Then, it is expected an agglomeration effect since activities are prone to cluster together in specific locations (King, 1984). Tourism research evidences the existence of external economies of scale (e.g., specialized suppliers in tourism), feeding a cumulative cycle that reinforces the size of the market area.

For this context, hotels tend to be located close to each other to increase supply, improve efficiency and survive (Barros, 2005, Yang et al., 2012). By applying this theory, the positive relationship between agglomeration degree and hotel’s benefit has been supported (Chung and Kalnins, 2001, Canina and Harrison, 2005). Furthermore, given that the existence of hotels in an area may increase the attractiveness of the location, nor the type of hotel establishments located in a certain location, nor the intensity of their agglomeration will necessarily be the same for all price levels, which is why it is useful to know the effects of competition for different hotel price levels. Though the theory is not exempt of critics, advocates claim its rationality to explain tourism location decisions (Daniels, 2007).

2.4. Electronic Word of Mouth

Online tourism marketing channels have experienced faster growth than other channels, with approximately one fifth of reservations being generated entirely online (Stangl et al., 2016). As a result, the Internet has produced a change of tourist behaviour, providing a high influence of eWOM on hotel industry and consumers (Cantallops and Salvi, 2014).

eWOM is a key determinant of consumer decisions (Duan et al., 2008), and its influence is particularly notable in the restaurant and hospitality industries (e.g., Ye et al., 2009). Evidence shows that the effect of eWOM on price can be as important as hotel category (Pawlicz and Napierala, 2017), and in dynamic pricing contexts, eWOM (as online reputation according to Tsang and Prendergast, 2009) is even more important than hotel category (Abrate and Viglia, 2016).

Consumer opinion offers greater confidence than communications from a company itself (Vermeulen and Seegers, 2009). Even a numerical rating generates more reliability to prospective customers who are willing to pay more for products with a high rating (Nielsen, 2012). In addition, the publication of ratings and customer comments on tourist accommodation company websites is used by these same businesses to change their prices (Yacouel and Fleischer, 2012, Ögüt and Onur, 2012).

From the empirical studies of the effects of eWOM on hoteliers' decisions, it has been found that for those online intermediaries with a positive reputation, the information provided by their customers generates a hotel price premium (Yacouel and Fleischer, 2012). The positive effect of eWOM on hotel occupancy (Viglia et al., 2016) and willingness to pay premium prices for accommodation (Nieto-García et al., 2017) have also been evidenced. Thus, it is clear that opinions published about a hotel can be a determining factor in hotel pricing.

2.5. Country location

From a management point of view, behavioral decision making varies across different countries (Laurent, 1983). Thus, the importance of market factors has been highlighted to explain differences in productivity between countries (Jones and Romer, 2009), diversity in the success factors of Total Quality Management (Sila and Ebrahimpour, 2003), and differences in business management styles and how those differences generate variations in productivity (Bloom and Van Reenen, 2010).

In hotel management research, the quality signals in each country that can influence hotel prices have been identified (Abrate et al., 2011). Several works have revealed the existence of differences in hotel management in terms of property management (Pine and Phillips, 2005), human, cultural, market, social and labor management resources between countries (Nankervis and Debrah, 1995). Also, Lee (2011) shows that there are attributes associated with the country, such as economic performance or total inbound tourists, that affect hotel pricing. Even, the city of destination influences hotel rates (Abrate et al. 2012; Baldassin et al., 2017).

3. Methodology

3.1. Research setting

The research covers four European countries with thriving tourism activity: France, Spain, Italy and the United Kingdom. In all of them, the tourism industry contributes significantly to the country economies, but the greatest contribution occurs in Spain (Table 2).

	International tourist arrivals	International tourism inbound receipts (US $ Millions)	Average receipts per arrival (US $)	Travel & Tourism Competitiveness Index
France	84,451,621	45,920	543.7	2^{nd}
Spain	68,521,255	56,468	824.1	1^{st}
Italy	50,731,770	39,449.2	777.6	8^{th}
UK	34,435,840	45,463.6	1,320.2	5^{th}

Table 2.

Key Indicators in tourism industry

Source: UNWTO (2018) and World Economic Forum 2017

3.2. Data collection and variables

The database was built with a combination of web analysis techniques with data from the information system of international Group Travel Agencies (GTA) (Becerra et al., 2013, Paulizt and Napierala, 2017). Thus, an initial sample of 14,772 hotels was obtained from the four countries considered. Finally, due to the existence of missing data in the initial database, the sample was reduced to 3,800 hotels located in 163 cities and organized in 1,221 commercial zones defined by the GTA. Since the final sample covers geographical areas of different sizes, the commercial zone was considered as a geographical competition area because the hotels located within each zone are considered commercially homogeneous within their category.

The information from the GTA provides greater advantages for its comparability, homogeneity and breadth (Abrate and Viglia, 2016, Paulizt and Napierala, 2017). In this case, we have selected the GTA: Veturis.com, which has recently been included in the “1000 Companies to inspire Europe” (London Stock Exchange Group 2017). With bounce rate, page views/user and time on site (minutes) as a references (www.alexa.com, accessed 2 July 2018), Veturis’s bounce rate is lower than that of the most popular OTAs and its page view/user and time on site are only lower than those of booking.com. Similarly, Veturis tops Google searches in real time ranking through keywords such as ‘travel agency’ and ‘tourism intermediaries, remaining ahead of its competition (www.serprobot.com).

Additionally, the information about price and hotel attributes included in the sample was retrieved from the hotel websites (Paulizt & Napierala, 2017).

Since room price may experience variations caused by the distribution channel, the season or the holding of commercial events, in accordance with previous studies (Hung *et al.* 2010, Zhang et al., 2011b), the average room rate for a standard double room is considered herein as a dependent variable. Furthermore, a semi-logarithmic model (Rosen, 1974) was used to describe the impact of the explanatory variables on price. Specifically, the explanatory variables were defined as follows:

- **Hotel category.** This variable is represented by five dummy variables for the five common star categories (from one to five stars), and the category “Other” used as the reference (Masiero et al., 2015).

- **Hotel local competition.** Two variables are used to represent a hotel’s competence level (Becerra et al., 2013), which ideally should incorporate several dimensions of spatial competition. The first variable, N_Hotels, measures the concentration effect of the area and is computed as the total number of hotels with the same category in the same commercial area. The second, Distance, describes the intensity of agglomeration and is estimated as the average distance of each hotel from all other hotels in its area. For this purpose, the geographical distance between competitors in the same commercial area was calculated using their GPS coordinates and with routines programmed in R. Thus, the resulting variable measures (km), the average distance of a hotel with respect to the other hotels with the same category in its area (Becerra et al., 2013). The consistency of the values obtained was checked and verified.

- **eWOM.** A reputational approach, based on Zhang et al. (2011b) was used. This variable measures the average valuation made by the customers of each hotel. This rating made by the customers and published on the web portal is a numerical valuation between zero (the worst evaluation) and ten (the best evaluation).

- **Country**. Dummy variables were used to incorporate hotels countries. More specifically, said dummy variables we considered for France, Italy and UK. Therefore, Spain was considered as the reference country.

In addition to the independent variables above, we also included the following control variables:

- **Hotel size.** We controlled for hotel size using the number of rooms in every hotel. It is expected a significant effect on room price (Becerra et al., 2013).

- **Hotel type.** We controlled for hotel type identifying the different type of lodgings in the setting analyzed (aparthotel, hostel, hotels and other types of establishments) by three dummy variables with the last category used as the reference. These variables capture objectively the types and level of services and amenities of the hotel.
- **City hotel.** Since there are significant differences on price between city hotels and hotels located outside urban areas (Falk and Hagsten 2015), this dummy variable was used to control location effect.

Descriptive statistics are contained in Appendix A.

3.3. Data analysis

In order to analyze what characteristics can influence room prices, the proposed regression model is given by:

$$LNPRICE = \alpha_0 + \sum_{i=1}^{3} \beta_i Z_i + \sum_{i=1}^{5} \gamma_i S_i + \sum_{i=1}^{3} \omega_i X_i + \sum_{i=1}^{5} \theta_i C_i$$

where C_i denotes the control variables, Z_i the country dummy variables, S_i the category dummy variables, X_i the continuous variables (eWOM, N_Hotels, Distance). The coefficient ω_i of a continuous variable, multiplied by 100, provides the percentage of influence on room price, whereas for a dummy variable (coefficients β_i, γ_i) the percentage effect on room price is computed by $100 \cdot \left(e^{\beta_i} - 1\right)$ (Halvorsen and Palmquist, 1980).

The statistical analyses included in this study were obtained using the statistical software R version 3.3.2 and the package ‘quantreg’ (Koenker, 2017).

Table 3 shows the main descriptive statistics of continuous variables, while Table 4 shows the hotel distribution by category and country.

	Mean	St. dev.	Median	Min	Max
LNPRICE	4.303	0.503	4.210	3.018	7.110
eWOM	7.431	1.208	7.600	0.200	10
N_Hotels	24.84	50.763	7	1	331
Distance	1.728	2.017	1.170	0	25.95

Table 3.

Sample descriptive statistics.

Category\Country	France	Spain	Italy	UK
1*	1.372	3.689	1.780	1.967
2*	24.871	12.466	6.825	8.852
3*	49.399	34.447	37.092	37.377
4*	21.612	43.534	47.181	46.885
5*	0.857	3.417	3.561	4.590
Others hotel establishments	1.887	2.447	3.561	0.328

Table 4.

Hotels distribution by category and country (%)

Firstly, we analysed the existence of endogeneity issues related to reputation variable (eWOM) by using different sets of instrumental variables (see analysis in Appendix B). After reviewing literature about eWOM, the instrumental variables considered in the different sets are Age of hotel, Ecological hotel (Kim et al., 2017), Dinner à la carte (Gu and Ryan, 2008), Availability of terrace in room, and Entertainment activities (Fernandes and Fernandes, 2018). Following Semadeni et al. (2014), the effectiveness of endogeneity tests depends on instrumental quality (strong and exogenous instruments). The F test for weak instruments rejected, in all cases, the null hypothesis of weak instruments at the one percent level. Additionally, the Sargan test confirmed that the instruments are exogenous in all cases. Finally, in all cases the Wu-Hausman test shows that there are no endogeneity issues related to the variable eWOM.

Next, we tested the existence of multicollinearity using the variance inflation factor (VIF). VIF values for all independent variables are below 2.1, so no multicollinearity was detected. Next, we considered the estimation of the regression model by applying OLS. Shapiro-Wilk and Shapiro-France tests confirmed the non-normality of the residuals. In addition, the Breusch-Pagan test (Hung et al., 2010) shows heterocedasticity in the model.

Thus, the OLS assumptions are not satisfied and consequently the OLS estimators may be less efficient. Moreover, the maximum average room price is sixty times higher than the minimum average room price for the sample, which suggests asymmetry of the hotel price distribution. The asymmetry is confirmed by a positive skewness value of 5.96. Based on these reasons, we considered the use of quantile regression, which is an appropriate method of estimation with asymmetric variables and long-tail distributions because it considers a weighted sum of absolute residuals and its estimates are robust to outliers (Koenker and Bassett, 1978). Futhermore, quantile regression estimates the conditional quantile functions and makes it possible to analyze whether a specific independent variable has a different effect on the conditional distribution of the dependent variable. Thus, quantile regression provides a full representation of conditional distribution.

The quantile regression model is given by:

$$\mathrm{y_i} = \mathrm{x_i'}\beta_\theta + \mathrm{u}_{\theta \mathrm{i}}$$

where $\theta \in (0,1)$ is the quantile, yi the dependent variable, xi a vector of explanatory variables, uθi the residuals vector and βθ the vector of parameters to be estimated. Then, so that Quant_θ (y_i |x_i)=x_i^' β_θ by minimization of

$$\min_{\beta} \sum_{y_i \geq x_i\beta_\theta} \theta |\, y_i - x_i\beta_\theta| + \sum_{y_i < x_i\beta_\theta} (1-\theta) |\, y_i - x_i\beta_\theta|$$

To estimate this, we considered the Frisch-Newton method (Portnoy and Koenker, 1997) and applied the Feng et al. (2011) bootstrap method to obtain standard errors estimates for the parameters.

For the goodness of fit for quantile regression, we considered the Wald test proposed in Koenker and Bassett (1982b) and the pseudo R^2 value defined in Koenker and Machado (1999).

4. Results

Figure 1 shows the effect of each explanatory variable throughout the price distribution (from quantile 0.01 to 0.99). The solid horizontal line at zero represents the null effect.

The dashed horizontal lines with the solid line represent OLS estimate. The shaded region is a 95% point-wise confidence band for quantile regression coefficients.

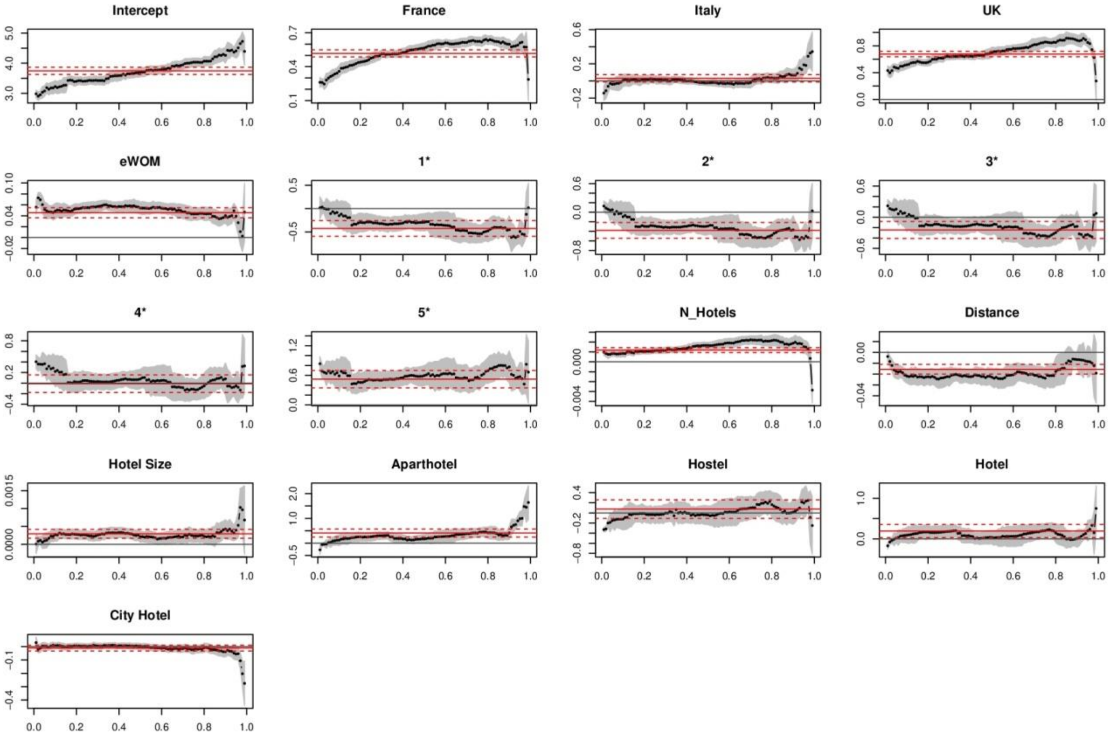

Figure 1.

Estimated coefficients with quantile regression for room price (by quantile)

To analyze the influence of explanatory variables throughout the price distribution, it is common to estimate using quantile regression at the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of the dependent variable (Masiero et al., 2015). Figure 1 shows variables (France, Italy and Distance) whose effect at the 1st percentile is different with respect to the 10th percentile, as it also displays other variables (France, UK, N_Hoteles) whose effect at the 99th percentile is different with respect to the 90th percentile. Therefore, we included the results at the 1st and 99th percentiles.

Table 5 shows the coefficients estimated by OLS and quantile regression at the considered percentiles. Additionally, Table 5 provides the pseudo R2 value and the Wald test (F-statistic) proposed in Koenker and Bassett (1982b). The Wald test contrasts if the full model is significant respect to the model with only control variables. Results reveal that the full model is significant in all cases.

	OLS	Quantile						
		0.01	0.1	0.25	0.5	0.75	0.9	0.99
Intercept	3.745***	2.982***	3.225***	3.412***	3.703***	4.034***	4.262***	4.394***
France	0.517***	0.261***	0.359***	0.475***	0.566***	0.624***	0.599***	0.287**
Italy	0.030	-0.143**	4.8E-3	0.019	-0.021	0.019	0.067	0.343***
UK	0.678***	0.431***	0.516***	0.617***	0.706***	0.859***	0.882***	0.275
eWOM	0.046***	0.056***	0.048***	0.055***	0.054***	0.043***	0.040***	0.046
1*	-0.426***	0.017	-0.152	-0.289***	-0.294***	-0.538***	-0.451***	0.018
2*	-0.381***	0.130*	-0.093	-0.286***	-0.289**	-0.526***	-0.371**	0.030
3*	-0.246**	0.220**	0.015	-0.137	-0.153	-0.357***	-0.176	0.075
4*	-0.012	0.404***	0.219	0.046	0.077	-0.117	0.079	0.324
5*	0.524***	0.836***	0.589***	0.512***	0.595***	0.562***	0.772***	0.666**
N_Hotels	1.2E-3***	9.8E-4***	8.5E-4***	1.1E-3***	1.7E-3***	2.2E-3***	1.8E-3***	-2.9E-3***
Distance	-0.016***	-3.8E-3	-0.022***	-0.025***	-0.023***	-0.024***	-6.7E-3	-0.019
Hotel Size	2.9E-4***	4.9E-6	2.7E-4***	2.5E-4***	2.1E-4**	2.3E-4**	4.2E-4**	6.8E-4
Aparthotel	0.407***	-0.271*	0.120	0.257**	0.171*	0.403***	0.409**	1.640***
Hostel	0.076	-0.330*	-0.122	-0.040	-0.045	0.187	0.014	-0.250
Hotel	0.194**	-0.172*	0.090	0.159	0.037	0.199*	0.010	0.751**
City Hotel	-0.010	0.030	6.9E-3	5.1E-4	0.4E-4	-0.025	-0.038	-0.276**
R^2	0.388	0.178	0.192	0.221	0.259	0.284	0.275	0.139
F, $H_0:\beta_i=0$	179.94***	40.812***	64.846***	130.2***	152.28***	146.3***	110.14***	10.885***

* p<0.1

** p<0.05

*** p<0.01

Table 5.

Regression coefficients with OLS and quantile regression.

The OLS results show that all variables, except Italy and 4*, have a significant effect on price. Coefficients for category confirm a positive effect of hotel category on price, that is, higher hotel category implies higher price. The results show that “Other hotel establishments” have a similar price to four-star hotels, significantly higher than one-star, two-stars and three-stars hotels (34.69%, 31.68% and 21.81% respectively) and significantly lower than five-star hotels (68.88%). For country variables, results show that Spanish and Italian hotels have similar prices while France and UK have a significantly higher price than Spain or Italy (67.70% and 96.99%, respectively). The variable eWOM has a positive effect on price, meaning an incremental point in the valuation of a hotel increases the room price by 4.6%. Finally, the positive effect of the variable N_hotels on price combined with the negative impact of the variable Distance confirm that hotel concentration has a positive relationship with room price.

The quantile regression results show that each explanatory variable is significant at some of the quantiles considered, emphasizing France, 5* and N_Hotels with significant effect at all quantiles. Furthermore, Wald test for slope equality (Koenker and Bassett 1982a) shows that the effect of all independent variables differs across quantiles, except for 5*, whose impact is constant over the conditional distribution of the room price (Table 6).

	0.01, 0.1	**0.1, 0.25**	**0.25, 0.5**	**0.5, 0.75**	**0.75, 0.9**	**0.9,0.99**
France	7.6E-3***	1.5E-6***	5.3E-5***	9.2E-3***	0.261	1.6E-3***
Italy	0.029**	0.653	0.036**	0.177	0.277	0.205
UK	0.427	7.0E-3***	0.011**	8.5E-6***	0.573	5.4E-6***
eWOM	0.408	0.218	0.879	0.076*	0.676	0.732
1*	0.809	0.377	0.917	0.017**	0.684	0.451
2*	0.748	0.195	0.997	0.018**	0.463	0.308
3*	0.769	0.317	0.800	0.043**	0.397	0.601
4*	0.790	0.253	0.630	0.054*	0.357	0.604
5*	0.723	0.644	0.287	0.805	0.360	0.845
N_Hotels	0.646	0.092*	8.1E-4***	2E-3***	0.245	2.8E-5***
Distance	1.3E-4***	0.283	0.629	0.815	3.4E-3***	0.570

* p<0.1
** p<0.05
*** p<0.01

Table 6.

Wald test, significant differences of slope among quantiles

The category coefficients estimated with quantile regression and Figure 1 both display the positive effect of the hotel category. Similarly, non-category establishments (i.e., no stars) have similar prices to one-star hotels and are significantly positioned below all other categories at the 1st percentile. For all quantiles, these hotels display prices significantly lower than five-star hotels, in some cases similar to the rest of categories (10th and 90th), or similar to the three-star and four-star hotels (25th, 50th and 90th) or only similar to four-star hotels (75th).

For country variables, results show that French hotels display a significantly higher price than Spanish hotels at all quantiles. The same goes for British hotels, except at the 99th percentile, where British and Spanish prices are similar. The difference between French and British prices with respect to Spanish price varies across quantiles (Table 6). Furthermore, Italian hotels have significantly lower prices than Spanish hotels at the 1st percentile (13.32%) while Italian prices are higher than Spanish prices at the 99th percentile (40.92%). Generally, UK hotels have the highest price at all quantiles, but the highest price is from Italy at the 99th percentile.

eWOM has a significant positive effect on room price except at the 99th percentile. Table 6 displays a non-constant impact of eWOM throughout the price distribution. Finally, regarding competition, the variable N_Hotels has a significantly non-constant effect, displaying a positive relationship with price except at the 99th percentile, where the effect is negative. The variable Distance has a non-constant effect throughout the price distribution, with a significant negative effect on price at all quantiles, except at 1st, 90th and 99th percentiles. Thus, the concentration–price relationship is positive, except at the 99th percentile, where a lower number of competitors results in higher prices.

5. Conclusions

Based on a sample data set of 3,800 hotels in four European countries, this paper analyzes the influence of hotel category, country of location, eWOM received by hotel customers and hotel spatial competence by modeling hotel price through OLS and quantile regression. Data have been obtained through a multisource procedure.

It must be noted that there are differential effects for all explanatory variables except for five-star category. For all quantiles, estimations provide support to the positive effect of the category on the price, verifying the heterogeneity of the effect. Furthermore, hotels included in ‘Other hotel establishments’ offer a similar price to the three and four-star price at certain price levels. The case of 5-star hotels proves to be unique in that only the category is linked to the price when the latter is very high. Even more, a particularly different behavior is revealed at the 99th percentile with respect to the rest of quantiles.

The effect of eWOM is significant, reveling eWOM as an explanatory variable in all the quantiles/price levels, with a significant effect (except for the 99th percentile).

Results also confirm the significant effect of hotel country location and show the competitiveness in prices of hotels in Spain and Italy, compared to hotels located in France and the UK. The highest prices correspond, at all price levels except the 99th percentile, to the UK, followed by the hotel prices in France, while Spanish and Italian hotels only present price differences at the 1st percentile. Italian hotels are more competitive than Spanish hotels, with the exception of the 99th percentile, where Spanish hotels have lower prices. These results suggest that there is a high quality/price ratio attributed to hotel country location and that European destinations located in Western Europe (France, the UK) tend to be more expensive than destinations in Southern Europe (Spain, Italy), with the exception of the 99th percentile, where Italian hotels display the most expensive prices. This result is consistent with an external hotel price index such as the one provided by Deloitte-STR Global and Smith Travel Research Inc. (2017), which measures average room rates calculated for first-class branded hotels.

6. Discussion

A first contribution of this study is to extend pure hedonic models focused on hotel attributes and amenities, or that do not contemplate differentiated effects over price distribution. Quantile regression estimation is justified especially in the presence of an asymmetric dependent variable, allowing the identification of heterogeneous effects throughout the distribution.

Another interesting contribution is related to the link between country location and price competitiveness. Specific country factors are to be considered to account for differences in prices for hotels with similar categories.

Regarding the effect of eWOM, it should be noted that the large sample used in the study and the full range of hotels covered contribute to overcoming previous studies (Yen and Tang, 2019).

As theoretical implications, these results confirm the applicability of Signaling Theory but only as a first approach, albeit imprecisely. eWOM is considered as a complementary quality signal to hotel category. These results suggest the existence of information asymmetries and indicate that hoteliers may adopt additional quality signals to justify pricing decisions (Nicolau and Sellers, 2010). Besides, analysis of price as asymmetric variable shows heterogeneity of explicative variables effects, questioning the validity of the Tisdell's model.

Concerning the applicability of CPT to hotel pricing, the results of the spatial competence variables confirm its assumptions, though for the 99th quantile is not confirmed, because the price decreases when the number of competitors increases.

Hotels could benefits of a location with high concentration of competition, as relationship is positive. Previous studies found a weak negative effect of the number of competitors on the price, therefore suggesting that the number of competitors should not be so decisive (Falk and Hagsten, 2015). Our study confirms evidences that negative effects of competition –reduction in prices, can be compensated with benefits of increasing occupation, which thereby improves hotel performance (Chung and Kalnins, 2001, Canina et al., 2005). It should be noted that for the 99th percentile, the effect of the number of competitors is negative, so location at this price level is preferable in low concentration locations.

Some managerial implications can be drawn. Hoteliers should take into account consumers' online assessments, paying special attention to those comments located on third-party websites. Though hotel category is a determinant of the rate, hotels managers should not allocate all their efforts only on obtaining an upgrade of their hotel category, as there are other categories in which price level is similar to three and four-star hotels.

Location decisions have considerable consequences for pricing. Commercial zone with other hotels of similar category allows hoteliers to fix higher prices. However, as an exception, results reveal the possible existence of a substitution effect in the high-priced zone, with greater sensitivity. Also, evidences reveals differences in competitiveness between countries, with higher level for Spain and Italy compared to hotels located in France and the UK.

It is interesting to note the emergence of sharing economy as source of competition for hotels as research topic. Recent contributions find that while in hotels, category or attributes are essential variables, instead in sharing economy based accommodation host attributes (Wang and Nicolau, 2017), and reputational determinants are the critical variables (Abrate and Viglia, 2017).

This paper does feature several limitations that may encourage future research. Firstly, the present study incorporates hotel category and country location, but it would be interesting to consider the existence of regulatory differences to isolate and determine the validity of category as a price signal. Also, country-effect is only considered in the model through dummy variables. It would be interesting to incorporate variables related to cultural, historical or economic factors of each country. Secondly, other countries could be considered in order to obtain the universalization of results. Thirdly, the estimated model incorporates competition through the number of nearby hotels and distance. While this is an alternative and enlightening approach, results obtained should be investigated closely since other evidences in literature contradict the positive effect of the number of competitors on price (Becerra et al 2013). Such findings could indicate that the effect of the number of competitors is non-linear, requiring alternative model specification. Another limitation is related to the static approach of this modeling, in comparison with a dynamic approach based on available room more than hotels per se. Additionally, a future line of research is to determine whether the aggregation of hotels in zones can create shared knowledge and, therefore, be a source of competitive advantage (Pinch et al., 2003). Finally, other measurements of eWOM can be incorporated in order to achieve a generalization of results (Yen and Tang, 2019).

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Appendix A: Sample descriptive statistics.

	Mean	St. dev.	Median	Min	Max
First Price Quartile					
eWOM	7.099	1.113	7	0.200	10
N_Hotels	14.72	44.244	4	1	331
Distance	1.538	1.995	0.915	0	17.890
Second Price Quartile					
	Mean	St. dev.	Median	Min	Max
eWOM	7.425	1.091	7.6	2	10
N_Hotels	21.75	52.535	5	1	331
Distance	1.748	2.134	1.210	0	25.95
Third Price Quartile					
	Mean	St. dev.	Median	Min	Max
eWOM	7.569	1.24	7.9	2	10
N_Hotels	28.95	52.627	10	1	331
Distance	1.88	1.966	1.46	0	11.98
Fourth Price Quartile					
	Mean	St. dev.	Median	Min	Max
eWOM	7.632	1.305	7.9	2	10
N_Hotels	33.92	51.156	13	1	268
Distance	1.746	1.958	1.070	0	17.92

Table A.1.

Sample descriptive statistics by price quartile.

Category\Country	France	Spain	Italy	UK
First Price Quartile				
1*hotels	6.818	7.125	7.792	6.667
2*hotels	47.727	22.85	22.078	33.333
3*hotels	36.363	44.349	48.052	53.333
4*hotels	0	22.604	16.883	6.667
5*hotels	0	0	0	0
Others hotel establishments	9.091	3.071	5.195	0
Second Price Quartile				
Category\Country	France	Spain	Italy	UK
1*hotels	0	3.268	0	11.111
2*hotels	48.718	10.850	2.247	27.778
3*hotels	44.872	37.908	52.810	50
4*hotels	5.128	45.621	40.449	5.556
5*hotels	0	0.392	0	0
Others hotel establishments	1.282	1.961	4.494	5.556
Third Price Quartile				
Category\Country	France	Spain	Italy	UK
1*hotels	1.183	1.309	0	4.478
2*hotels	28.994	5.237	2.913	11.940
3*hotels	48.521	27.823	33.009	62.687
4*hotels	18.343	60.393	59.223	19.403
5*hotels	0.592	3.273	1.942	1.493
Others hotel establishments	2.367	1.964	2.913	0
Fourth Price Quartile				
Category\Country	France	Spain	Italy	UK
1*hotels	1.027	1.039	0	0
2*hotels	12.671	5.195	1.471	4.390
3*hotels	53.082	17.143	10.294	26.829
4*hotels	31.164	56.883	72.059	62.439
5*hotels	1.370	16.883	14.706	6.341
Others hotel establishments	0.685	2.857	1.471	0

Table A.2.

Quartile Hotels distribution by category and country (%)

Appendix B: Endogenity analysis

Diagnostic tests	df1	df2	Statistic	p-value
Weak instruments	2	3782	19.401	4.1E-9***
Sargan	1		0.853	0.356
Wu-Hausman	1	3782	2.366	0.124

* p<0.1

** p<0.05

*** p<0.01

Table B.1: eWOM endogeneity diagnostic with the instrumentals variables Age and Availability of terrace.

Diagnostic tests	df1	df2	statistic	p-value
Weak instruments	3	3781	13.369	1.1E-8***
Sargan	2		3.832	0.147
Wu-Hausman	1	3782	1.719	0.190

* p<0.1

** p<0.05

*** p<0.01

Table B.2: eWOM endogeneity diagnostic with the instrumentals variables Age, Availability of terrace and Ecological Hotel.

Diagnostic tests	df1	df2	statistic	p-value
Weak instruments	4	3780	10.027	4.5E-8***
Wu-Hausman	1	3782	1.709	0.191
Sargan	3		4.878	0.181

* p<0.1

** p<0.05

*** p<0.01

Table B.3: eWOM endogeneity diagnostic with the instrumentals variables Age, Availability of terrace, Ecological Hotel and Dinner á la carte.

Diagnostic tests	df1	df2	statistic	p-value
Weak instruments	5	3779	8.459	5.7E-8***
Wu-Hausman	1	3782	1.727	0.189
Sargan	4		4.879	0.300

* p<0.1

** p<0.05

*** p<0.01

Table B.4: eWOM endogeneity diagnostic with the instrumentals variables Age, Availability of terrace, Ecological Hotel, Dinner á la carte and Entertainment activities.