International Journal of Hospitality Management 79 (2019) 140–147

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

Tourism seasonality, online user rating and hotel price: A quantitative approach based on the hedonic price model

Xinrui Wang[a,b], Jiuxia Sun[a,b], Haizhen Wen[c,d,*]

[a] School of Tourism Management, Sun Yat-Sen University, Guangzhou, 510275, China
[b] Center for Leisure, Tourism and Social Development, Sun Yat-Sen University, Guangzhou, 510275, China
[c] Department of Civil Engineering, Zhejiang University, Hangzhou 310058, China
[d] Center for Real Estate Studying, Zhejiang University, Hangzhou 310058, China

ARTICLE INFO

Keywords:
Hedonic price model
Tourism seasonality
Online user rating
Hotel prices
Quantile regression
China

ABSTRACT

The paper aims to investigate the relationship between tourism seasonality, online user ratings and the determinants of hotel prices based on the hedonic price model using the online dataset of hotels in Sanya, China. The empirical results of ordinary least squares (OLS) and quantile regressions both show that hotel prices are highly related to tourism seasonality. Compared to the low season, hotel prices increase by 23.1% in the high season and by 159.9% during Chinese New Year. Online user ratings demonstrate heterogeneous impacts on both location and time dimensions in hotel pricing. The quantile regressions further indicate that hotels with higher prices are less sensitive to seasonality and that the online user rating plays a more important role for mid- and low-priced hotels by mitigating the negative seasonal effects on hotel prices. Our findings provide new evidence supporting the current literature and offer useful implications for hospitality management.

1. Introduction

Tourism is a major industry in many cities, and the hotel industry usually contributes the most to tourism revenue (Hung et al., 2010). Hotel prices fluctuate greatly with seasonality (Juaneda et al., 2011), especially during peak periods such as holidays and major events (Herrmann and Herrmann, 2014). Seasonality is a problematic aspect for many tourist destinations (Jang, 2004) and usually refers to a temporal imbalance in demand that may be expressed in terms of the number of tourists, their expenditure, and the number of nights booked at a hotel (Butler, 2001). Since in tourist destinations, hotel pricing varies with tourism demand, analyzing the changes in hotel prices provides a useful approach to examine tourism seasonality. The products and services provided by a hotel are heterogeneous, and thus hotel prices are influenced by many factors. The hedonic price model assumes that heterogeneous products comprise inherent characteristics, and the model is widely applied to studies on pricing determinants (Lancaster, 1966; Rosen, 1974; Thrane, 2007; Alegre et al., 2013). This paper investigates the influence of factors related to the inherent characteristics on hotel prices in different periods to reflect the effects of seasonality based on the hedonic price model.

With the rapid development of social media and technological platforms, online booking is prevalent in the hospitality sector. Tourists are increasingly relying on online ratings to make accommodation purchase decisions (Gavilan et al., 2018), and the role of online reputation is becoming more and more important in hotel pricing (Anderson, 2009; Schamel, 2012; Serra and Salvi, 2014). Some scholars have noticed the impact of online user ratings on hotel prices (O'Connor, 2010; Casaló et al., 2015) and have analyzed its moderating effect between locational characteristics and hotel prices (Yang et al., 2016). However, online user ratings may also demonstrate heterogeneous impacts on the time dimension when considering the seasonality of tourism. On the one hand, demand for a hotel is extremely high during peak seasons, such that many tourists must book hotels in advance. Online booking is convenient, and increasing numbers of tourists are inclined to book hotels via the internet (Blomberg-Nygard and Anderson, 2015). If online booking in advance is the choice of most tourists during the high season, then online user ratings will have greater impacts on hotel premiums. On the one hand, previous studies have shown that hotels with good reputations, such as those belonging to a branded chain, are less affected by tourism seasonality (Espinet et al., 2012). Online user rating is also a reflection of the hotel's reputation, and whether it has a similar heterogeneous effect needs to be further discussed. However, the possible heterogeneous impacts caused by online user ratings have been overlooked in most of the relevant literature.

* Corresponding author at: Center for Real Estate Studying, Zhejiang University, Hangzhou 310058, China.
E-mail addresses: wang.xinrui@foxmail.com (X. Wang), sunjx@mail.sysu.edu.cn (J. Sun), ningduwhz@hotmail.com (H. Wen).

https://doi.org/10.1016/j.ijhm.2019.01.007
Received 8 June 2018; Received in revised form 20 December 2018; Accepted 7 January 2019
0278-4319/ © 2019 Elsevier Ltd. All rights reserved.

To fill this research gap, our paper employs a hedonic price model to identify the determinants of hotel prices and their impacts during different periods and further investigates the heterogeneous impacts of online user ratings on time dimensions based on a dataset from Sanya, China. Sanya, located in Hainan Province, is one of the largest sun-and-sand holiday resorts in China. Since China is the world's most populous country, research based on the Chinese tourist market will provide important implications for tourism and hospitality management. Additionally, most studies based on the hedonic price model are conducted using ordinary least squares (OLS) regressions, which do not reflect the changes in variables in different quantiles. We introduce quantile regressions into our analysis of hotel prices to solve this problem, and empirical studies employ both OLS and quantile regressions. In general, our paper makes the following contributions. First, we discuss the seasonality of tourism through the changes in hotel prices and provide a complete description of the determinants of hotel prices in different periods using quantile regressions. Second, this paper investigates the heterogeneous impacts of online user ratings, including the moderating effect on the hotel's locational characteristics and the heterogeneity of tourism seasonality, which is rarely mentioned in the existing literature. Third, this is one of the first attempts to introduce the hedonic price model into tourism and hospitality research in China, and the extraordinary peak seasons formed by the tremendous Chinese tourist market will provide new evidence for the current research. The remainder of this paper is organized as follows. Section 2 provides a brief review of previous relevant studies. Section 3 outlines the framework of our study. Section 4 presents our empirical study and its main findings. Section 5 is the conclusion.

2. Literature review

Hedonic price theory was created and developed over decades to identify the implicit prices embedded in heterogeneous products. There are two main approaches that have contributed to the theoretical work on hedonic prices (Chau and Chin, 2003): one approach is derived from Lancaster's (1966) consumer theory, and the other approach comes from the model put forward by Rosen (1974). Both approaches emphasize that heterogeneous products comprise a myriad of inherent attributes. Consumer demand for goods is not based on the products themselves but rather on the characteristics/attributes contained in the products; the combination of these attributes affects the utility of consumers and thus influences consumers' willingness-to-pay (Lancaster, 1966; Rosen, 1974). Since the characteristics/attributes of heterogeneous products have implicit prices that cannot be directly observed, the hedonic price model provides a method of calculating those implicit prices and is widely used in many fields related to the pricing of products, especially in the study of urban real estate prices and the assessment of nonmarket or public goods components (Goodman, 1978; Malpezzi, 2002; Sirmans et al., 2005).

The hedonic price model has been applied in tourism and hospitality research as well. Scholars have employed the hedonic price model to analyze the pricing of package tours (Thrane, 2005, 2007; Rigallitorrent and Fluvià, 2011; Alegre et al., 2013), ski-lift ticket prices (Falk, 2008), and hotel room prices (Espinet et al., 2003; Monty and Skidmore, 2003; Lee and Jang, 2011; Juaneda et al., 2011). The implicit prices estimated by the hedonic price model reflect real consumer willingness-to-pay, which offers a relatively objective way to analyze the determinants of hotel prices. Previous studies based on the hedonic price model have focused on many aspects of hotel characteristics (Callan, 1998; Israeli, 2002; Zhang et al., 2011; Lee and Jang, 2012; Alegre et al., 2013; Yang et al., 2016). Generally, the attributes related to hotel prices could be categorized into internal and external factors (Chen and Rothschild, 2010). Internal factors contain the facilities and services provided by the hotel, and the relevant attributes include but are not limited to, the following factors: franchising/chain (Wu, 1999; White and Mulligan, 2002); star rating (Thrane, 2007; Israeli, 2002); hotel age (Hung et al., 2010); scale (White and Mulligan, 2002; Alegre et al., 2013); hotel amenities, such as a swimming pool (Rigallitorrent and Fluvià, 2011; Yang et al., 2016), parking lot (Espinet et al., 2003) and fitness center (Andersson, 2010; Chen and Rothschild, 2010); and internet accessibility (Schamel, 2012). External factors refer to the location characteristics of the hotel, such as the distance from the airport (Lee and Jang, 2011), the distance to the center of the tourist resort (Alegre et al., 2013) and the hotel's surroundings (Rigallitorrent and Fluvià, 2011).

In addition to internal and external factors, seasonality and online user ratings are very much related to hotel room prices and have been discussed in relevant literature (O'Connor, 2010; Espinet et al., 2012; Yang et al., 2016). The impact of seasonality on hotel prices is obvious and has been verified by many studies (Juaneda et al., 2011; Rigallitorrent and Fluvià, 2011). Some studies have further explored the relationship between seasonality and pricing strategies for different hotels and shown more interesting findings. For example, scholars have noted that hotels with higher star rating or hotels that belong to a branded chain usually offered fewer discounts in the off-season, indicating smaller seasonal price variations, even in sun-and-beach destinations (Espinet et al., 2012; Becerra et al., 2013), whereas lower-quality hotels would offer more frequent discounts in the low season (Lee and Jang, 2013). However, tourism seasonality is not the focus of most hotel pricing research, and relevant studies either avoid the seasonality effect by using data from a single, specific period (Andersson, 2010; Schamel, 2012) or control for the time effects but do not delve into the interaction between seasonality and the hotel's characteristics (Masiero et al., 2015). In addition, the study of the seasonality caused by peak periods, such as holidays and major events, has been overlooked to some extent. Herrmann and Herrmann (2014) studied the changes in the price of rooms during Oktoberfest in Munich and found that the event affected the daily price level as well as price differentials among hotels and that prices differ across hotels mainly due to the star category and the proximity to the event. However, discussions of tourism seasonality and hotel prices remain limited and must be further explored.

On the other hand, online user ratings and reviews are becoming increasingly important in tourism and hospitality research, as is the popularity of online booking in the hospitality industry. Online user ratings can significantly affect customers' attitude toward a hotel as well as their purchasing decisions (Vermeulen and Seegers, 2009; Sparks and Browning, 2011; Chan et al., 2017; Gavilan et al., 2018) and is very much related to hotel room price (Anderson, 2012; Zhang et al., 2011; Phillips et al., 2017). As a kind of quality signal, online user ratings reflect the reputation of a hotel, and thus a higher online user rating would generate a higher premium (Zhang et al., 2011; Yacouel and Fleischer, 2011; Phillips et al., 2017). The aforementioned studies also pointed out that the impact of online user rating on hotel room price was heterogeneous, that it would be stronger for a midscale property than for a luxury hotel (Anderson, 2012). Online user ratings would also show moderating effects on locational characteristics. For example, Yang et al. (2016) found that low market accessibility leads to lower hotel prices, but this influence could be mitigated by a positive reputation as represented by online user ratings. However, their study did not investigate the heterogeneity of online user ratings while considering the time dimension. The possible heterogeneous impacts of online user ratings on hotel prices during different periods are overlooked in most studies, and there is no in-depth discussion of the relationship between online user ratings and tourism seasonality.

Additionally, current research based on the hedonic price model is mostly conducted using ordinary least squares (OLS) regressions. This approach can only provide an incomplete description of a conditional distribution (Mosteller and Tukey, 1977) and cannot obtain the coefficients of the independent variables for the entire regression as a function of the change in hotel prices. The quantile regression proposed by Koenker and Bassett (1978) can somewhat address this problem.

Compared to the OLS method, quantile regression is less sensitive to outliers and more efficient when the error term is non-normal (Buchinsky, 1998). For the study of hotel prices, quantile regression provides a more flexible and complete characterization of the determinants of hotel prices at the higher and lower tail of the distribution (Hung et al., 2010; Masiero et al., 2015). Huang et al. (2010) applied the quantile regression approach to investigate the major determinants of hotel room pricing strategies and reported some detailed findings; specifically, that factors such as hotel age and market conditions were the only significant determinants in the high-price category. Thus, to provide a complete description of the determinants of hotel prices in different periods, it is necessary to conduct the hedonic price model using quantile regressions.

In summary, research on the determinants of hotel prices is rich, but tourism seasonality is one of the least concerned aspects, especially involving the study of peak periods. Online user ratings have significant impacts on hotel prices, whereas their heterogeneous impacts, especially those on the time dimension, are rarely mentioned in most studies. On this basis, our research focuses on the following questions yet to be explored: i) how does tourism seasonality, especially the seasonality caused by holidays and major events, affect hotel prices? and ii) what is the role of online user ratings in hotel pricing? Are there any heterogeneous impacts, especially the heterogeneous impacts on the time dimension, when considering tourism seasonality? The hedonic model provides an appropriate approach to address these issues. Moreover, applying quantile regressions to the hedonic price model can further reveal the differentiated effects of seasonality and online user rating along the distribution of hotel prices. Thus, our study employs the hedonic price model with quantile regressions to analyze the relationship among tourism seasonality, online user ratings and the determinants of hotel prices.

3. Research design and data collection

We use the dataset of hotels in Sanya, China, to conduct this study. Sanya, located in the southernmost part of Hainan Province, is the most important island tourist destination in China. Sanya is a tropical marine monsoon climate zone, with an average annual temperature of 25.7 °C. There are some famous bays in Sanya, including Sanya Bay, Coral Bay, Yalong Bay, Yazhou Bay, Dadonghai Beach, Haitang Bay, Sunny Bay and others. Sanya welcomes a large number of tourists each year and is known as the "Chinese Hawaii." The main tourist market for Sanya is China, and 96% of overnight visitors were from China in 2017, according to the statistical data of the Sanya Statistics Bureau. However, because of the climate, tourism in Sanya reveals the effects of seasonality. Fig. 1 demonstrates the number of overnight visitors and the average hotel occupancy rate for each month in 2017. The peak season continues from November through April of the following year. During these months, most cities in China are relatively cold and tourists prefer to go on vacations in Sanya. During Chinese New Year, Sanya is usually the first choice for most family vacations, forming the highest peak of tourism in Sanya. However, from May to October the number of tourists and the average hotel occupancy rate in Sanya both decrease to some extent due to its hot weather. Thus, Sanya is a typical case study of tourism seasonality and tourist markets in China.

There are more than 3000 hotels in Sanya, but most hotels have no star rating. To follow a unified evaluation standard, we chose three-star, four-star and five-star hotels in Sanya as our samples. We obtained a list of 346 hotels from an online travel agency in China using the website www.ctrip.com, including 122 three-star hotels, 93 four-star hotels and 131 five-star hotels. To measure the dependent variable, hotel price, we used the average daily room price for one week to reduce the random fluctuation that occurs in a single day. Considering that the hotel booking price fluctuates with time and that different rooms have different prices, we searched on Ctrip.com for the one-week advance-booking price and collected the lowest price for double occupancy as the daily room price. We used these data to calculate the average room price for one week. To reflect tourism seasonality in Sanya, we selected three different one-week stays: 25–31 January 2018 (high season), 15–21 February 2018 (Chinese New Year) and 7–13 May 2018 (low season). For the 346 selected hotels, we obtained their room prices during the above three periods, yielding a set of 1033 observations after removing the missing values.[1]

The independent variables used in the hedonic price model can be classified into internal and external attributes. The external attributes refer to the hotel location and the tourist resources surrounding the hotel, as suggested in previous studies (Espinet et al., 2003; Lee and Jang, 2011; Rigallitorrent and Fluvià, 2011; Alegre et al., 2013). We therefore assess the following three external factors:

Distance from the airport. The distance between the hotel and the airport reflects the accessibility of the hotel. As the distance increases, hotel prices should decrease, according to the studies of Lee and Jang (2011) and Alegre et al. (2013). This variable is measured by the straight-line distance between the hotel and the airport on the map in kilometers.

Distance to the center of the tourist resort. Hotel rates around the core tourist resort are usually higher (Alegre et al., 2013). Sanya, as a tourist destination, has numerous tourist resorts. Among them, Yalong Bay is the most famous and attracts the majority of the tourists in Sanya. We measure the straight-line distance between the hotel and Yalong Bay on the map in kilometers as the proxy variable.

Beach. The number of beaches around the hotel has a positive effect on prices (Espinet et al., 2003; Rigallitorrent and Fluvià, 2011; Alegre et al., 2013). Since the famous beaches in Sanya are scattered, we use a dummy variable representing whether there is a beach near the hotel as the measure. Specifically, $beach = 1$ means that within 2 km of the hotel there is at least one of the well-known beaches in Sanya, including Sanya Bay, Yalong Bay, Dadonghai Beach, Haitang Bay, and Wuzhizhou Island; otherwise, $beach = 0$.

The internal attributes refer to the star rating, the affiliation with hotel chains, hotel age, the number of rooms, hotel amenities and other factors (White and Mulligan, 2002; Espinet et al., 2003; Thrane, 2007; Hung et al., 2010; Chen and Rothschild, 2010; Yang et al., 2016). Star rating, as a universal rating system, is correlated with hotel attributes, such as the hotel's size, facilities, services, and room prices. As a result, there is a multicollinearity between the star rating and the internal attributes of the hotel (Thrane, 2005). Thus, the star rating is not used as an independent variable in our paper. The selected internal attributes are as follows:

Chain: A dummy variable representing whether the particular hotel belongs to a chain. If the hotel is a chain affiliation, then the dummy variable is $chain = 1$; otherwise, $chain = 0$. According to the study conducted by Yang et al. (2016), we define a hotel as a chain if the parent company holds more than 30 individual hotels.

Hotel age: A variable measuring the years during which the hotel has been operational (Hung et al., 2010).

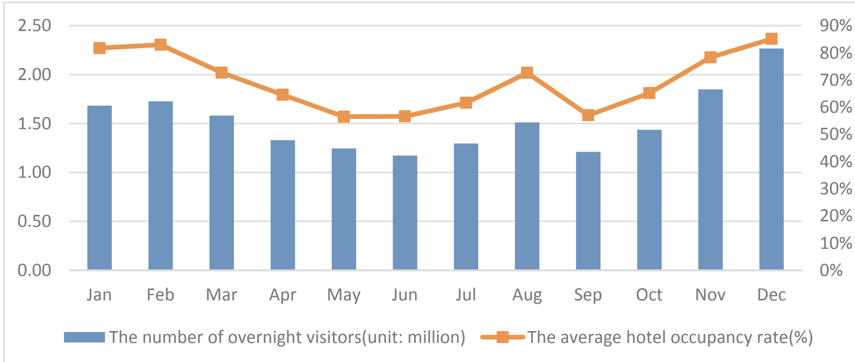
No. of rooms: A variable showing the total number of rooms available in the hotel (White and Mulligan, 2002; Alegre et al., 2013).

Room size: A variable referring to the area of the double occupancy room, measured using square meters (Heo and Hyun, 2015).

Breakfast: A dummy variable indicating the availability of a free breakfast (Chen and Rothschild, 2010; Lee and Jang, 2011); $breakfast = 1$ indicates the availability of a free breakfast, and $breakfast = 0$ indicates no free breakfast.

Pool: A dummy variable indicating the presence of a swimming pool in the hotel (Andersson, 2010; Chen and Rothschild, 2010; Rigallitorrent and Fluvià, 2011; Yang et al., 2016); if there is a

[1] Three hotel price data points during the 15-21 February period and two hotel price data points during the 7-13 May period are missing; as a result, there are five missing values in total.



Source: The data were obtained from the Sanya Statistics Bureau.

Fig. 1. The number of overnight visitors and the average hotel occupancy rate for each month in 2017.
Source: The data were obtained from the Sanya Statistics Bureau.

swimming pool on-site, then *pool* = *1*; otherwise, *pool*=*0*.

Spa: A dummy variable indicating the presence of a spa at the hotel. If there is a spa on-site, then *Spa* = *1*; otherwise *Spa*=*0*.

Fitness: A dummy variable indicating whether there is a fitness center in the hotel (Andersson, 2010; Chen and Rothschild, 2010); *fitness* = *1* indicates that the hotel has a fitness center, and *fitness* = *0* indicates that no fitness center is available.

Children: A dummy variable indicating whether there are facilities for children in the hotel; *children* = *1* indicates the presence of facilities for children, and *children* = *0* indicates that there are no such facilities.

Parking: A dummy variable indicating the presence of a parking lot (Chen and Rothschild, 2010). If there is a parking lot on site, then *parking* = *1*; otherwise, *parking*=*0*.

In addition to the internal and external attributes, our study mainly focuses on the impacts of tourism seasonality and online user ratings. Tourism seasonality can be measured during the selected periods. Here, *Period* is a nominal variable showing the week associated with the room price (Rigallitorrent and Fluvià, 2011; Yang et al., 2016), namely: *period* = *1* for the week of January 25–31, 2018, representing the high season of tourism in Sanya; *period* = *2* for the week of February 15–21, 2018, when Chinese New Year occurs; *period* = *3* for the week of May 7–13, 2018, reflecting the comparatively low season for tourism in Sanya.

Online user ratings are indicative of the word-of-mouth effect and reputation (O'Connor, 2010; Yang et al., 2016). The data from the hotel's online user ratings can be obtained from customer reviews at the website Ctrip.com, and the scale for the reviews ranges from 1.0 to 5.0, continuously. However, the ratings on Ctrip.com are highly clustered, with most hotels falling within the range of 4.0 and 4.8. Thus, it is better to normalize the initial online user rating data. We use the z-score method, and the normalization process is shown in Eq. (3.1).

$$z_i = \frac{a_i - \bar{a}}{s},\ \bar{a} = \frac{1}{n}\sum_{i=1}^{n} a_i,\ s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(a_i - \bar{a})^2}, \tag{3.1}$$

where, a_i is the initial online user rating collected from Ctrip.com, z_i is the normalized online user rating, and $\bar{a}$ and s represent the arithmetic mean and standard deviation, respectively.

On this basis, a semilogarithmic specification of the hedonic price model can be established in Eq. (3.2). The model is:

$$Ln(y_i) = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki} + \mu_i, \tag{3.2}$$

where y_i represents the average daily room price in the selected period. We employ a semilogarithmic model to build a stable linear relationship, while the natural logarithm form of hotel price (lnP_i) is used in the estimations. Independent variables are represented by x_{ki}, in which the continuous variables, such as the distance from the airport (*Lnairport*), the distance to the center of the tourist resort (*Lnresort*), and the room size (*Lnsize*), are used in the natural logarithm forms as well. The coefficients of x_{ki} are represented by β_k.

We further examine the detailed relationship between hotel price and selected variables based on the quantile regressions. The quantile regression is used to estimate the conditional median function, which is obtained by minimizing the sum of absolute residual instead of the squared residual as performed by the OLS method (Hallock and Koenker, 2001). Thus, the basic quantile regression can be written as follows:

$$Q_\theta(y_i|x_{ik}) = min\sum_i \theta \left|Ln(y_i) - \left(\alpha + \sum_k \beta_k(\theta)x_{ki}\right)\right| + \sum_i (1-\theta)\left|Ln(y_i) - \left(\alpha + \sum_k \beta_k(\theta)x_{ki}\right)\right| \tag{3.3}$$

where $\theta \in (0,1)$ is the estimated conditional quantile, $Q_\theta(y_i|x_{ik})$ represents the θ^{th} conditional quantile of y_i given x_{ik}. $\beta_k(\theta)$ represents the vector of parameters to be estimated.

A summary of the selected variables and their descriptive statistics are listed in Table 1. The descriptive statistics reveal some basic information about the samples. For example, only 18.3% of the hotels are affiliated with a hotel chain in the sample, and 70% have at least one beach nearby. Additionally, 18.9% of the hotels offer free breakfast to the customer, and 72.9% have a swimming pool. A fitness center can be found in 62.8% of hotels, and a spa is available in 57% of hotels. Facilities for children are offered by 43% of hotels, and 81.8% of hotels have a parking lot. The average online user rating is 4.524, reflecting a

Table 1
Descriptive statistics of variables.

Variable	Description	Mean	Std. Dev.
LnP_i	The logarithm of the average daily room price in one week	6.558	0.849
Lnairport	The logarithm of the distance from the airport	2.537	0.852
Lnresort	The logarithm of the distance to the center of the tourist resort (Yalong Bay)	2.605	0.960
beach	Whether there is a beach near the hotel	0.700	0.460
chain	Whether the hotel belongs to a chain	0.183	0.387
age	The years that the hotel has been operating	5.733	4.960
LnNOR	The logarithm of the number of rooms available	4.830	1.071
Lnsize	The logarithm of room size	3.754	0.589
breakfast	Whether the price includes a free breakfast	0.189	0.392
pool	Whether the hotel has a pool	0.729	0.451
Spa	Whether the hotel has a spa	0.570	0.501
fitness	Whether the hotel has a fitness center	0.628	0.484
children	Whether the hotel has children facilities	0.430	0.495
parking	Whether the hotel has a parking lot	0.818	0.386
rating	The online user rating of the hotel	4.524	0.363
z_rating	The normalized online user rating of the hotel	−0.0026	1.0006

Table 2
The estimation results of the hedonic price models with OLS [LnP_i = dependent variable].

Variable	Model 1: January Coefficient (t-value)	Model 2: February Coefficient (t-value)	Model 3: May Coefficient (t-value)	Model 4: all samples Coefficient (t-value)
Lnresort	−0.177***	−0.177***	−0.122**	−0.159***
	(-7.581)	(-7.233)	(-5.095)	(-11.461)
beach	0.122**	0.201***	0.112**	0.148***
	(2.396)	(3.792)	(2.337)	(4.926)
chain	0.167***	0.166***	0.168***	0.167***
	(2.957)	(2.772)	(2.899)	(4.964)
Lnsize	0.545***	0.552***	0.490***	0.529***
	(13.563)	(13.158)	(11.924)	(22.248)
breakfast	0.259***	0.259***	0.250***	0.256***
	(4.436)	(4.261)	(4.176)	(7.410)
Spa	0.157***	0.187***	0.146***	0.163***
	(2.989)	(3.409)	(2.708)	(5.249)
fitness	0.101*	0.153**	0.045	0.100**
	(1.673)	(2.438)	(0.733)	(2.796)
children	0.206***	0.062	0.118**	0.129***
	(3.622)	(1.050)	(2.035)	(3.832)
parking	0.056	0.019	0.151**	0.075*
	(0.867)	(0.279)	(2.287)	(1.965)
z_rating	0.142***	0.182***	0.066**	0.130***
	(5.586)	(6.890)	(2.532)	(8.656)
Period = 1				0.231***
				(2.902)
Period = 2				1.599***
				(35.082)
Constant	4.052***	5.169***	4.043***	4.092***
	(21.417)	(26.206)	(20.949)	(36.144)
Adjust R^2	0.671	0.655	0.655	0.777
N	346	343	344	1033

Notes: T-statistics are shown in the brackets. ***, ** and * denote significance at the 1, 5, and 10% level, respectively.

relatively high customer satisfaction with the hotels in Sanya.

4. Empirical findings

We first examine the hotel's hedonic price in the three different periods with OLS regressions. Models 1–3 are conducted based on the data in January, February and May, respectively, and the regression results are shown in Table 2. Models 1–3 are employed with all the independent variables selected in Section 3. Some variables, including *Lnairport, age, LnNOR* and *pool* are not significant in these models, and their results are not listed in Table 2. The adjusted R^2 of Models 1–3 are 0.671, 0.655, and 0.571, respectively. We also tested the variance inflation factor (VIF) of each variable. The values of centered VIF are much smaller than 10, which suggests that the problem of multicollinearity is not serious, and the correlations between variables would be acceptable in our study.

In general, the regression results indicate that the distance to Yalong Bay and the accessibility to beaches can significantly influence hotel price. The variable *Lnresort*, which is measured by the distance to Yalong Bay, is significant at a 1% level, with the coefficients of -0.177, -0.177 and -0.122 in the different periods, indicating that with a 1% decrease in the distance to Yalong Bay, the hotel price will increase by 0.177% in January and February and by 0.122% in May. Accessibility to the beach can also significantly increase hotel rates, given that customers are willing to pay more for a hotel with a beach nearby. Additionally, the variable representing the distance from the airport is not significant, which is probably because most of the hotels in the samples provide pick-up service and customers are less sensitive to the distance from the airport.

Regarding the internal attributes, *chain*, *room size*, *breakfast* and *spa* all have significant impacts on hotel rates in all three periods. *Fitness center*, *facilities for children* and *parking lot* also have significant impacts during either one or two periods. According to the results, the room price of a chain hotel is approximately 16.7% higher than that of an unaffiliated hotel; for every 1% increase in room size, the hotel price increases between 0.490% and 0.552% during various periods. If the hotel provides a free breakfast, hotel rates will increase by approximately 25%. Additionally, the amenities, such as the *spa*, *fitness center*, *facilities for children* and *parking lot*, will also raise the hotel rates to some extent. The normalized online user ratings are significant at the 1% level, and the coefficients in Models 1–3 are 0.142, 0.182 and 0.066, respectively, which means an increase in the normalized rating results in a hotel price increase of 14.2% in January, 18.2% in February and 6.6% in May. This finding indicates that online user ratings have a positive impact on hotel prices, and the extent of this impact may vary in different periods.

Model 4 is conducted using all the samples in the three periods, in which the low period (*period = 3*) is the reference group and the other two periods are set as independent variables (*period = 1 and period = 2*). The results are also shown in Table 2. The adjusted R^2 is 0.777, showing a better fitting model. In Model 4, the variables in *period = 1* and in *period = 2* are both significant at the 1% level. The coefficient of *period = 1* is 0.231, indicating that hotel prices would be 23.1% higher in the high season (January) than in the low season (May). The coefficient of *period = 2* is 1.599, showing that during Chinese New Year, hotel prices increased by 159.9%, more than twice the cost in the low season (May). The results illustrate the seasonality of Sanya's hotel prices. On the one hand, the hotel rates in the off-season are lower compared to the peak season; on the other hand, hotel prices increase sharply during Chinese New Year. The estimation results of the other variables are very similar to those of Models 1–3, *Lnresort*, *beach*, *room size* and *z_rating*, and the other hotel amenities all have significant impacts on hotel rates.

We further employ the interactive models to assess the heterogeneous impacts of online user ratings on both location and time dimensions. We establish four interaction terms between online user rating and other variables, namely: 1) *rating×January*, representing *z_rating* multiplied by *period = 1*; 2) *rating×February*, representing *z_rating* multiplied by *period = 2*, to reflect the heterogeneous effect on tourism seasonality; 3) *rating×resort*, representing *z_rating* multiplied by *Lnresort*; and 4) *rating×beach*, representing *z_rating* multiplied by *beach*, to measure the moderating effect on locational characteristics. Models 5–8 are conducted using the four interaction terms, respectively. The results are shown in Table 3.

The interaction term *rating×January* in Model 5 is significantly positive at the 1% level, and the coefficient is 0.007, which indicates that if the online user rating of a hotel increases by 1%, the hotel room price will increase by an additional 0.7% in the high season. The coefficient of *rating×February* is 0.089 in Model 6, showing that if the online user rating of a hotel increases by 1%, the hotel room price will increase by an additional 8.9% during Chinese New Year. In other words, the hotel with a higher online user rating will raise its room price even more during peak seasons. This increase may be because tourists usually choose to book hotels on the internet in advance during peak seasons, and the impact of online user ratings will be greater. The coefficient of *rating×resort* is 0.058, while the coefficient of *Lnresort* is -0.163 in Model 7, indicating that a higher online user rating would mitigate the negative effect of *Lnresort*. Specifically, if a hotel's online user rating increases by 1%, the negative impact of the distance from Yalong Bay on hotel prices will be weakened by 5.8%. This result means that a well-established online reputation can mitigate the negative impact of a hotel's location to some extent, which is consistent with the findings of Yang et al. (2016). The interaction term *rating×beach* is not significant in Model 8, meaning that the level of the online user rating cannot influence the beach's impact on hotel rates.

The hedonic price models with quantile regressions are further conducted with the entire dataset. We use the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles to provide a relatively complete characterization of the

Table 3
The estimation results with interaction terms [LnP_i = dependent variable].

Variable	Model 5: *rating × January* Coefficient (t-value)	Model 6: *rating × February* Coefficient (t-value)	Model 7: *rating × resort* Coefficient (t-value)	Model 8: *rating × beach* Coefficient (t-value)
Period = 1	0.233***	0.233***	0.233***	0.232***
	(2.899)	(2.989)	(2.955)	(2.895)
Period = 2	1.558***	1.559***	1.562***	1.559***
	(35.786)	(34.477)	(35.807)	(35.253)
Lnresort	−0.153***	−0.152***	−0.163***	−0.160***
	(−10.439)	(−10.846)	(−10.044)	(−11.463)
beach	0.153***	0.156***	0.158***	0.142***
	(4.997)	(5.078)	(5.321)	(4.786)
chain	0.167***	0.166***	0.164***	0.167***
	(5.019)	(4.951)	(4.947)	(4.965)
Lnsize	0.526***	0.525***	0.524***	0.528***
	(22.252)	(22.401)	(22.314)	(22.248)
breakfast	0.256***	0.257***	0.258***	0.256***
	(7.411)	(7.536)	(7.569)	(7.467)
Spa	0.164***	0.165***	0.166***	0.163***
	(5.318)	(5.432)	(5.410)	(5.307)
fitness	0.099***	0.099***	0.098***	0.100**
	(2.797)	(2.796)	(2.787)	(2.768)
children	0.130***	0.131***	0.132***	0.128***
	(3.902)	(3.971)	(3.982)	(3.827)
parking	0.074**	0.075**	0.075**	0.075*
	(1.949)	(1.973)	(1.975)	(1.965)
z_rating	0.308***	0.298***	0.310***	0.165***
	(6.739)	(7.183)	(6.497)	(7.367)
rating × January	0.007*			
	(1.871)			
rating × February		0.089***		
		(3.100)		
rating × resort			0.058***	
			(5.048)	
rating × beach				0.001
				(0.050)
Constant	4.121***	4.099***	4.027***	4.090***
	(36.732)	(34.878)	(35.890)	(36.057)
Adjust R^2	0.778	0.782	0.784	0.777
N	1033	1033	1033	1033

Notes: T-statistics are shown in the brackets. ***, ** and * denote significance at the 1, 5, and 10% level, respectively.

determinants of the hotel prices. According to our samples, the 10th, 25th, 50th, 75th, and 90th quantiles of the average hotel room prices represent 40USD, 60USD, 100USD, 180USD and 350USD, respectively. The results at the different quantiles are shown in Table 4. The coefficients of *Lnairport* and *age* are not significant in all conditional quantiles and not listed in the table.

The results of quantile regressions are consistent with the OLS regressions in general but also have different effects in some respects. The positive impact of *period = 1* does not emerge when the quantile regression is evaluated at the 90th quantile, showing that hotels with higher prices are less sensitive to seasonality. Meanwhile, *period = 2* is significantly positive in all conditional quantiles, indicating that all hotels would sharply raise room prices during Chinese New Year. The coefficient gradually decreases with an increase in hotel prices, showing that the increase in the hotel rates during Chinese New Year is even greater for low-priced hotels.

Regarding the internal attributes, the impacts of *chain*, *room size*, *breakfast* and *spa* are larger in the high-priced hotels than in the mid- and low-priced hotels, which reveals that the higher the price of the hotel, the higher the revenue generated by its chain and the hotel amenities. Although the impact of *pool* is not significant when conducting OLS regressions, this variable shows a positive impact on hotel prices in quantile regressions. The impact of *pool* becomes increasingly significant with a decrease in hotel rates, indicating that for the low-priced hotels, providing a swimming pool in the hotel would generate a more marginal effect on hotel rates. The number of rooms also shows significantly positive effects in low-priced hotels, mostly because the number of rooms is related to the hotel scale, and an increase in hotel scale would drive up room rates to some extent for low-priced hotels.

The impacts of online user ratings are significantly positive; thus, a well-established online reputation brings a greater premium to all hotels. The interaction term *rating × January* only has a significant positive effect on mid- and low-priced hotels, indicating that online user ratings are more important for these hotels in coping with seasonality. The interaction term *rating × February* shows the significant impact on hotel rates in all quantiles, and its coefficient increases with the quantiles. This result means that during Chinese New Year, the impacts of the online user rating on room rates would be greater for high-priced hotels. The impacts of *rating × resort* are significantly positive in all conditional quantiles. The coefficient first increases with the rise in hotel prices, and then decreases to 0.011 after the quantile regression is evaluated at the 75th quantile hotel. This result means that the online user rating can mitigate the negative impact of the distance from Yalong Bay on hotel prices, and these moderating effects are greater for mid-priced hotels. From the above results, it can be inferred that a well-established online reputation is much more important for mid- and low-priced hotels. High-priced hotels can release quality signals through star ratings and brands, and thus the impact of online user ratings is limited.

5. Conclusions

This paper discusses the relationship between tourism seasonality, online user ratings and the determinants of hotel prices in Sanya using a

Table 4
The results of the hedonic price models with quantile regressions [LnP_i= dependent variable].

Variable	10th quantile	25th quantile	50th quantile	75th quantile	90th quantile
Period = 1	0.153*	0.259**	0.221***	0.116***	0.053
	(1.898)	(2.577)	(2.752)	(2.770)	(0.832)
Period = 2	1.478***	1.639***	1.543***	1.317***	1.201***
	(41.038)	(32.166)	(27.658)	(27.911)	(21.339)
Lnresort	−0.157***	−0.139***	−0.125***	−0.137***	−0.118***
	(−10.630)	(−7.410)	(−5.160)	(−6.540)	(−4.260)
beach	0.184***	0.147***	0.164***	0.111**	0.081
	(5.690)	(4.530)	(3.610)	(1.990)	(0.970)
chain	0.160**	0.227***	0.182***	0.201***	0.256***
	(2.252)	(5.340)	(3.640)	(5.100)	(3.140)
LnNOR	0.101***	0.099**	0.102	0.089	0.097
	(3.740)	(2.140)	(1.370)	(0.611)	(0.340)
Lnsize	0.351***	0.446***	0.499***	0.572***	0.607***
	(5.770)	(11.930)	(19.050)	(12.790)	(13.490)
breakfast	0.188***	0.178***	0.207***	0.267***	0.342***
	(3.670)	(4.580)	(5.630)	(4.210)	(3.210)
pool	0.145***	0.064*	0.083*	0.042**	0.130
	(3.050)	(1.920)	(1.960)	(2.060)	(1.530)
Spa	0.092**	0.071*	0.102**	0.158***	0.226***
	(2.410)	(1.800)	(2.080)	(2.660)	(2.900)
fitness	0.054	0.105**	0.051	0.092	0.105
	(1.230)	(2.500)	(1.170)	(1.180)	(1.630)
children	0.122**	0.126***	0.189***	0.126**	0.119**
	(2.340)	(2.990)	(4.830)	(2.020)	(2.450)
parking	0.080*	0.116**	0.121**	0.117	−0.005
	(1.750)	(2.510)	(2.490)	(1.640)	(-0.050)
z_rating	0.176*	0.196***	0.193**	0.209***	0.198***
	(1.930)	(2.680)	(2.600)	(3.550)	(3.700)
rating × January	0.018**	0.037**	0.032***	0.013	0.009
	(2.047)	(2.562)	(3.056)	(1.325)	(1.043)
rating × February	0.032*	0.069**	0.078*	0.061*	0.125***
	(1.983)	(2.420)	(1.840)	(1.870)	(3.160)
rating × resort	0.020*	0.037*	0.048***	0.080***	0.011***
	(1.823)	(1.850)	(2.750)	(3.950)	(3.226)
rating × beach	0.006	0.054	0.052	0.027	−0.062
	(0.271)	(1.310)	(1.410)	(0.830)	(0.317)
Constant	4.182***	4.057***	4.048***	4.116***	4.129***
	(14.930)	(27.540)	(29.950)	(23.340)	(21.920)
pseudo R^2	0.482	0.545	0.577	0.584	0.588
N	1033	1033	1033	1033	1033

Notes: T-statistics are shown in the brackets. ***, ** and * denote significance at the 1, 5, and 10% level, respectively.

quantitative approach based on the hedonic price model. The empirical findings show that in the external attributes, the distance to the tourist resort has a negative effect on hotel price, while the accessibility to beaches has a positive impact. The internal attributes, including chain, room size, free breakfast, and the presence of a spa, a fitness center, facilities for children and a parking lot would increase hotel prices at different levels. Hotel prices highly correlated with the seasonality of tourism. The results of OLS regressions show that hotel prices increased by 23.1% in the high season and 159.9% during Chinese New Year, compared to the low season in May. Online user ratings have significant positive impacts on hotel prices during all the periods. Meanwhile, the interactive models show that a hotel with a higher online user rating would raise its room price even more during peak seasons. The results also show the moderating effect of online user ratings on locational characteristics and indicate that a well-established online reputation can mitigate the negative impact of a hotel's location to some extent.

Quantile regressions were conducted to investigate the differentiated effects of the hotel's characteristics. Findings suggest that the impacts of the internal attributes, including chain, room size, free breakfast and the presence of a spa, are larger in high-priced hotels than in mid- and low-priced hotels, while the implicit price of a swimming pool is higher in mid- and low-priced hotels. All hotel prices rise sharply during Chinese New Year, and the extent of the increase is even greater in low-priced hotels. Meanwhile, the room prices of high-priced hotels barely fluctuate in the off-season, demonstrating that hotels with higher prices are less sensitive to seasonality. The results of the interaction terms show that a higher online user rating would generate more premiums for the high-priced hotels during Chinese New Year but would not generate significant impacts in other periods. However, for mid- and low-priced hotels, online user ratings can mitigate the negative impacts of both the hotel's location and the off-season on hotel prices; thus, a well-established online reputation is much more important to mid- and low-priced hotels, especially during the low tourism season.

Our findings provide new evidence supporting the existing literature. First, we studied the seasonality of tourism, which is one of the least understood aspects of tourism, from the perspective of changes in hotel pricing, and discussed the determinants of hotel prices during Chinese New Year, specifically by providing empirical evidence regarding tourist destinations in China. Second, the paper focused on the role of online user ratings in different periods and investigated the interaction between online user ratings and tourism seasonality for the first time. Empirical findings show the moderating impacts of online user ratings on both locational and temporal dimensions, which provides preliminary evidence of the heterogeneous effects of the hotel price determinants and offers avenues for future study. Third, we introduced the hedonic price model together with quantile regressions into our study of hotel pricing. This approach provides a complete description of the differentiated effects of a hotel's characteristics along the distribution of hotel prices, which is another contribution to current research. However, there remain some limitations. The three selected periods can largely reflect the seasonal effects of tourism, but cannot fully represent tourism seasonality or describe all of the seasonal changes in hotel prices. Thus, further studies should be carried out in this regard.

The findings provide some scientific implications for policymaking and hospitality management. On the one hand, tourism operators should notice the significant impact of tourism seasonality and develop marketing plans based on that seasonality. Local governments should take precautions and improve public services to cope with the numbers of tourists during the peak season. On the other hand, it is important for hotel managers to understand what attributes matter most to hotel prices. Our findings show that the determinants of hotel prices at the higher and lower ends of the distribution are different. For high-priced hotels, an upgrade of hotel amenities may result in a higher premium, and customers are inclined to pay more for these internal attributes. For mid- and low-range hotels, the online user rating is very important, as these hotels can hardly release quality signals through star ratings and brands. Thus, online reputation is an important way for these hotels of obtaining premiums and competitive advantages, and the management of these hotels should focus on improving hotel services and increasing customer satisfaction. Furthermore, mid- and low-range hotels should pay more attention to the risk of low occupancy when tourism decreases.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (No. 41701159) and the National Social Science Foundation of China (No. 15ZDB118).

References

Anderson, C.K., 2012. The impact of Social Media on Lodging Performance. Cornell Hospitality Rep. 12 (15), 4–11.
Alegre, J., Cladera, M., Sard, M., 2013. Tourist areas: examining the effects of location attributes on tour-operator package holiday prices. Tour. Manag. 38, 131–141.
Anderson, C.K., 2009. The billboard effect: online travel agent impact on Non-OTA reservation volume. Cornell Hospitality Reports.
Andersson, D.E., 2010. Hotel attributes and hedonic prices: an analysis of internet-based transactions in Singapore's market for hotel rooms. Ann. Reg. Sci. 44 (2), 229–240.
Becerra, M., Santaló, J., Silva, R., 2013. Being better vs. Being different: differentiation, competition, and pricing strategies in the Spanish hotel industry. Tour. Manag. 34 (43), 71–79.
Blomberg-Nygard, A., Anderson, C.K., 2015. United nations world tourism organization study on online guest reviews and hotel classification systems: an integrated approach. Serv. Sci. 8 (2), 139–151.
Buchinsky, M., 1998. The dynamics of changes in the female wage distribution in the USA: a quantile regression approach. J. Appl. Econom. 13 (1), 1–30.
Butler, R., 2001. Seasonality in tourism: issues and implications. Tour. Rev. 53, 18–24.
Callan, R.J., 1998. Attributional analysis of customers' hotel selection criteria by UK grading scheme categories. J. Travel. Res. 36 (3), 20–34.
Casaló, L.V., Flavián, C., Guinalíu, M., Ekinci, Y., 2015. Do online hotel rating schemes influence booking behaviors? Int. J. Hosp. Manag. 49, 28–36.
Chan, I.C.C., Lam, L.W., Chow, C.W.C., Fong, L.H.N., Law, R., 2017. The effect of online reviews on hotel booking intention: the role of reader-reviewer similarity. Int. J. Hosp. Manag. 66, 54–65.
Chau, K.W., Chin, T.L., 2003. A critical review of literature on the hedonic price model. Int. J. Housing Sci. Appl. 27, 145–165.
Chen, C.F., Rothschild, R., 2010. An application of hedonic pricing analysis to the case of hotel rooms in Taipei. Tourism Economics the Business & Finance of Tourism & Recreation 16 (3), 685–694.
Espinet, J.M., Saez, M., Coenders, G., Fluvià, M., 2003. Effect on prices of the attributes of holiday hotels: a hedonic prices approach. Tour. Econ. 9 (2), 165–177.
Espinet, J.M., Fluvià, M., Rigallitorrent, R., Saló, A., 2012. Hotel characteristics and seasonality in prices: an analysis using Spanish tour operators' brochures. Tour. Econ. 18 (4), 749–767.
Falk, M., 2008. A hedonic price model for ski lift tickets. Tour. Manag. 29 (6), 1172–1184.
Gavilan, D., Avello, M., Martinez-Navarro, G., 2018. The influence of online ratings and reviews on hotel booking consideration. Tour. Manag. 66, 53–61.
Goodman, A.C., 1978. Hedonic prices, price indices and housing markets. J. Urban Econ. 5 (4), 471–484.
Hallock, K.F., Koenker, R.W., 2001. Quantile regression. J. Econ. Perspect. 15, 143–156.
Heo, C.Y., Hyun, S.S., 2015. Do luxury room amenities affect guests' willingness to pay? Int. J. Hosp. Manag. 46, 161–168.
Herrmann, R., Herrmann, O., 2014. Hotel roomrates under the influence of a large event: the Oktoberfest in Munich 2012. Int. J. Hosp. Manag. 39 (2), 21–28.
Hung, W., Shang, J., Wang, F., 2010. Pricing determinants in the hotel industry: quantile regression analysis. Int. J. Hosp. Manag. 29, 378–384.
Israeli, A.A., 2002. Star rating and corporate affiliation: their influence on room price and performance of hotels in Israel. Int. J. Hosp. Manag. 21 (4), 405–424.
Jang, S.S., 2004. Mitigating tourism seasonality. Ann. Tour. Res. 31, 819–836.
Juaneda, C., Raya, J.M., Sastre, F., 2011. Pricing the time and location of a stay at a hotel or apartment. Tour. Econ. 17 (2), 321–338.
Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46, 33–50.
Lancaster, K.J., 1966. A new approach to consumer theory. J. Polit. Econ. 74, 132–157.
Lee, S.K., Jang, S.C., 2011. Room rates of U.S. airport hotels: examining the dual effects of proximities. J. Travel Res. 49 (2), 186–197.
Lee, S.K., Jang, S.C., 2012. Premium or discount in hotel room rates? The dual effects of a central downtown location. Cornell Hosp. Q. 53 (2), 165–173.
Lee, S.K., Jang, S.C., 2013. Asymmetry of price competition in the lodging market. J. Travel. Res. 52 (1), 56–67.
Malpezzi, S., 2002. Hedonic pricing models: a selective and applied review. Wisconsin-Madison CULER Working Papers, vol. 10. pp. 67–89.
Masiero, L., Nicolau, J.L., Law, R., 2015. A demand-driven analysis of tourist accommodation price: a quantile regression of room bookings. Int. J. Hosp. Manag. 50, 1–8.
Monty, B., Skidmore, M., 2003. Hedonic pricing and willingness to pay for bed and breakfast amenities in Southeast Wisconsin. J. Travel. Res. 42 (2), 195–199.
Mosteller, F., Tukey, J.W., 1977. Data Analysis and Regression. A Second Course in Statistics. Addison-Wesley Pub. Co.
O'Connor, P., 2010. Managing a hotel's image on TripAdvisor. J. Hosp. Mark. Manage. 19 (7), 754–772.
Phillips, P., Barnes, S., Zigan, K., Schegg, R., 2017. Understanding the impact of online reviews on hotel performance: an empirical analysis. J. Travel. Res. 56 (2), 235–249.
Rigallitorrent, R., Fluvià, M., 2011. Managing tourism products and destinations embedding public good components: a hedonic approach. Tour. Manag. 32 (2), 244–255.
Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. J. Polit. Econ. 82, 34–55.
Schamel, G., 2012. Weekend vs. midweek stays: modelling hotel room rates in a small market. Int. J. Hosp. Manag. 31 (4), 1113–1118.
Serra, C.A., Salvi, F., 2014. New consumer behavior: a review of research on eWOM and hotels. Int. J. Hosp. Manag. 36, 41–51.
Sirmans, G.S., Macpherson, D.A., Zietz, E.N., 2005. The composition of hedonic pricing models. J. Real Estate Lit. 13 (1), 3–43.
Sparks, B.A., Browning, V., 2011. The impact of online reviews on hotel booking intentions and perception of trust. Tour. Manag. 32 (6), 1310–1323.
Thrane, C., 2005. Hedonic price models and sun-and-Beach package tours. The Norwegian Case 43 (3), 302–308.
Thrane, C., 2007. Examining the determinants of room rates for hotels in capital cities: the Oslo experience. J. Revenue Pricing Manage. 5, 315–323.
Vermeulen, I.E., Seegers, D., 2009. Tried and tested: the impact of online hotel reviews on consumer consideration. Tour. Manag. 30 (1), 123–127.
White, P.J., Mulligan, G.F., 2002. Hedonic estimates of lodging rates in the four corners region. Prof. Geogr. 54 (4), 533–543.
Wu, L., 1999. The pricing of a brand name product: franchising in the motel services industry. J. Bus. Ventur. 14 (1), 87–102.
Yacouel, N., Fleischer, A., 2011. The role of cybermediaries in reputation building and price premiums in the online hotel market. J. Travel. Res. 51, 219–226.
Yang, Y., Mueller, N.J., Croes, R.R., 2016. Market accessibility and hotel prices in the Caribbean: the moderating effect of quality-signaling factors. Tour. Manag. 56, 40–51.
Zhang, Z., Ye, Q., Law, R., 2011. Determinants of hotel room price. Int. J. Contemp. Hosp. Manage. 23 (7), 972–981.