Análisis del impacto de Open Pricing dinámico en el Revenue Management Hotelero

Analysing the Impact of Dynamic Open Pricing on Hotel Revenue Management

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Abstract

The introduction of big data technology into hotel revenue management (RM) systems has paved a new way to fix prices in the hospitality industry called 'open pricing' (OP). This study analyses the evolution of dynamic pricing in hotels and examines the concept of open pricing. This pricing system is based on managing a large amount of data (big data) and consists primarily of sophisticated real-time dynamic pricing with no rate ranges and fences and depends on the customer's WTP. This study investigates whether the implementation of open pricing improves independent hotels' performance. Three case studies were conducted using an analysis of variance test to compare three years of data on three independent hotels after they started applying open pricing. The selected hotels' performance trends over time were also compared, via a t-test, with data about the competitors collected from STR. This study provides empirical evidence that open pricing improves the occupancy rate, average daily rate and revenue per available room, justifying its use in the RM systems of independent

hotels. It helps advance our understanding of the concept of open pricing and it is one of the few empirical studies to analyse the latter's impact on hotel performance.

Keywords: Open pricing; dynamic pricing; big data; independent hotels; revenue management.

Resumen

La utilización de la tecnología de big data en los sistemas de *revenue management* (RM) hoteleros ha introducido una nueva forma de fijar el precio en la industria hotelera denominada *open pricing* (OP). Este estudio analiza la evolución dinámica de los precios de los hoteles y examina el concepto de *open pricing.* Este modo de fijar los precios se basa en la gestión de una gran cantidad de datos (*big data*) que consiste principalmente, en una sofisticada aplicación de precios dinámicos en tiempo real sin rangos de tarifas, ni barreras o restricciones, basada en la disposición a pagar del cliente. Este estudio investiga si la implementación del *open pricing* aumenta el rendimiento de los hoteles independientes. Se realizaron tres estudios de caso utilizando la prueba de análisis de varianza para comparar tres años de datos en tres hoteles independientes después de aplicar *open pricing.* El desempeño de los hoteles seleccionados en las tendencias de tiempo con los datos de la competencia recopilados de STR también se comparó mediante la t test. Este estudio proporciona evidencia empírica de que OP mejora la tasa de ocupación, el precio medio diario y los ingresos por habitación disponible, lo que justifica el uso de *open pricing* en sistemas RM de hoteles independientes. Este estudio ayuda a avanzar en nuestra comprensión de la evolución de los precios dinámicos en la industria hotelera y el concepto *open pricing*; es el primer estudio empírico académico que analiza el impacto de *open pricing* en el desempeño del hotel.

Palabras clave: Open pricing; precio dinamico; big data; hoteles independientes; revenue management.

1 Introduction

Revenue management (RM) is a management philosophy used by companies with a fixed capacity, such as hotels, whose objective is to maximise the benefit and value offered to customers based on the analysis of information, price management and capacity management (Abad et al., 2019). One crucial hotel RM strategy is dynamic pricing (Vives and Jacob, 2021). It targets various segments of customers who are willing to pay (WTP) for their stay and match the product's features with their price preferences (Vives et al., 2018) by fluctuating the price according to variations in demand. In particular, hotels using a 'variable pricing' strategy (Rohlfs and Kimes, 2005) are facing new challenges due to technological advancements (Guillet, 2020). Wang et al. (2015) identified a knowledge gap in RM and "variable dynamic pricing" and contended that it should depend on the opportunities offered by big data instead of relying on historical and predicted demand analysis.

Theoretically, RM systems integrating big data improve real-time updates (Yeoman, 2020). This increased strategic data-driven to enhance revenue growth, enabling hotels to maintain unlimited price points (Xu et al., 2019) through open pricing (OP), which has evolved as a new dynamic pricing mechanism in hotels' RM (Guillet, 2020). OP prices all room types, channels and dates independent of each other instead of setting a predetermined tiered BAR price (Guillet, 2020; Talón-Ballestero et al., 2022). Variable pricing (Rohlfs and Kimes, 2005), another type of dynamic pricing, charges various nightly rates for the same room based on expected room demand using rate fences (Kimes and Wirtz, 2003). Rates are established in advance, usually one year in advance. Studies have investigated dynamic prices based on real-time value-based pricing, applying tariff barriers or fences (Al-Shakhsheer et al., 2017) and length of stay and type of room (Aydin and Birbil, 2018). However, fences prevent prices from being truly dynamic (Shapiro and Drayer 2014). Moreover, variable pricing is predetermined set rates according to fluctuation in demand. Variations are reflected in set price ranges and then remains fixed (Shapiro and Drayer 2014) and thus does not reflect actual consumer demand and client's WTP. OP, on the contrary, varies prices depending on fluctuations in demand without following ranges or fences and always takes advantage of the hotel's optimal price. Therefore, the demand curve can be fully optimised, and the bid price is more tailored to demand. The hotel sector trails behind other sectors in the use of

OP because of the lack of appropriate technology (HSMAI-Duetto, 2017), although professional studies demonstrate the effectiveness of OP (Duetto, 2018). González-Serrano and Talón-Ballestero (2020) and Talón-Ballestero et al. (2022) introduced OP to academia through theoretical and qualitative approaches. They called for a quantitative investigation into the impact of OP on hotel revenue. The current study contributes by answering this call.

Independent hotels lack advanced technology and highly skilled employees (Altin et al., 2017), making them less competitive than chains (O'Neill and Carback, 2011). However, they are crucial to economies and employment generation (Samujh and Devi, 2008). In Spain, independent hotels account for 80% of establishments and 45% of beds (INE, 2019). Consequently, they should be updated by efficient management, specifically RM. RM systems are now cloud based, which significantly reduces implementation costs (Talón-Ballestero et al., 2022). These new RM systems have introduced the concept of OP. To the best of our knowledge and despite the importance of OP's application in independent hotels, there is no empirical research on this topic. We address this gap by investigating the impact of OP on the independent hotels that contribute to its success.

This study aims to determine whether the application of OP improves the performance of the chosen hotels by differentiating between variable pricing and actual OP before (2017) and after (2018 and 2019) its implementation in the same hotels, using a longitudinal study of the occupancy rate (OR), average daily rate (ADR) and revenue per available room (RevPAR). The impact of competitive pressure (Becerra et al., 2013) is used as a control variable to try to eliminate external factors that may affect the change in revenue. The research methodology constructs three case studies of three independent hotels in Spain. The paper demonstrates that the application of OP can boost the selected independent hotels' revenues compared to variable dynamic pricing. The study finds statistically significant differences between the performance indicators of these hotels and those of their competitors. OP hotels show high variation in their performance to respond on the market.

2 Background and hypothesis development

2.1 Evolution of revenue management: from inventory control to open pricing

Over the last two decades, RM has evolved from inventory control to tactical pricing, to price optimisation solutions based on big data and, finally, to strategic RM (González-Serrano and Talón-Ballestero, 2020). Initially, RM was based on inventory control with short-term dynamic pricing strategies (Kimes, 2016). Spreadsheets and traditional RM systems were the only technology used. Forecasting relied on basic demand characteristics (e.g. seasonality and customer behaviour) and historical demand (Noone, 2016). Rates were varied by considering room types and restrictions by segment. Optimisation models revolved around aggregate demand, expected marginal seat revenue and bid price (Talluri and van Ryzin, 2004).

However, the raise of Internet made a new approach necessary (Yeoman, 2020). Thus, RM evolved towards dynamic pricing and incorporated competitor rates (Noone, 2016). Rates began to be determined based on demand forecasts, price elasticity and competition (Cross et al., 2009). The rise of online travel agencies and high price volatility led to the implementation of parity policies (Demirciftci et al., 2010), and different segments of customers were offered variations on a single BAR rate. Year ahead, BAR ranges were established, which fluctuated according to demand (Talón-Ballestero et al., 2011). Hotels then began to operate a floating BAR based on the various BARs realised during the customer's length of stay (Talón-Ballestero et al., 2011).

Consequently, RM is evolving into price optimisation through OP, where new technological advancements have allowed hotel management systems to overcome their reliance on a pre-established price scale. Open or agile pricing has infinite price points according to real-time fluctuations in demand and sophisticated price discrimination conducted by RM systems (Gonzáles-Serrano and Talón-Ballestero, 2020). This allows RM systems using a sophisticated algorithm to perform complex price discriminations for each tariff and day. Hence, OP presents the customer with better-adjusted pricing since it is based on real-time data about either the 'last room value' or maximum income for the last available room, together with the customer's WTP. It optimises all types of room rates (e.g., BARs, promotions, corporate rates and offers for different distribution channels), generating prices for each day (González-Serrano and Talón-Ballestero, 2020). The restriction of a specific day does not close reservations for the remaining days, in contrast to the BAR variable pricing,

which applies the restriction of a specific day uniformly and thus reduces booking availability if one of the combined days is not available. Therefore, OP enables hoteliers to keep bookings open for the week by reducing discounts, which is more efficient than the predetermined price model (González-Serrano and Talón-Ballestero, 2020).

The RM system consists of several modules. The first is a market intelligence module including market data (e.g., prices, reputation, quality, and parity). The second is a forecast module in which the 360-day OR, ADR and RevPAR are used to forecast room-type availability. The third is a recommendation module that provides price recommendations based on forecasting the rate-plan level and recommends a closing price level by segment and overbooking level. The algorithm works with a series of variables that influence the result depending on the availability of data that vary constantly in the RM system (Hoteltechreport, 2020).

RM systems outsourcing OP include IDeaS, Beonprice and Duetto (Abad et al., 2019). Some have been analysed based on the different aspects by which prices change by market segmentation (Vives et al., 2018; Baker et al., 2020). Internal segmentation in the hotel can be controlled in the short term, during which room prices and complementary products can be varied, while external segmentation cannot, such as the booking channel and physical attributes of the building. Differentiation between the short, medium and long term is based on the information (i.e. historical data) and experience required by the revenue manager, which allows the hotel to manage each of these segmentation components. Data on competitors also affect these components. For example, in the short term, a hotel will need data on competitors to set more accurate prices based on bookings or seasonality; however, such pricing could be based on the hotel's historical prices. By contrast, in the long term, competitor data will be necessary to segment the hotel's attributes correctly (e.g., if a three-star hotel wants to expand to four stars). This last segment includes online reputation. Finally, weather forecasting is closely linked to seasonality, although it can affect other components; for example, if the following weekend is expected to have good weather, hotels can raise their prices (Vives et al., 2018).

All RM systems are fed by the hotel's historical data or environment. This information is used in their algorithms. RM systems adopt three main types of information to fix prices: input,

output and interaction data. First, input data are important for forecasting. These include historical data, competitor pricing data, data on events and sometimes even data in IDeaS and Beonprice that take into account online reputation, all of which determine a hotel's market position. Additional information data, such as weather and flights, are not included in the RM system algorithm, although they can be introduced through specific rules. Data on regrets and denials are included only by Duetto (Hoteltechreport, 2020). Second, output data show forecasts by room type, cancellations and no-shows, as well as market segment. Moreover, they recommend prices at the rate-code level, prices by market segment, yield restrictions and overbooking limits (Beonprice, 2020). Finally, interaction data reflect the human–machine interface, including a recommendation override that allows revenue managers to manipulate the forecast. For example, in the case of the COVID-19 pandemic, revenue managers can add travel restrictions and microeconomic variables that influence demand. Moreover, these data include recommendations and forecasts by segment. Further, they allow users to override forecasts and managers to enter local events manually (Talón-Ballestero, et al.,2022).

The last step of strategic RM is the customisation of prices through loyalty programmes and corporate accounts based on the customer's lifetime value and customer value-based pricing. Thus, hotels can offer personalised prices (Talón-Ballestero, et al.,2022).

2.2 Dynamic pricing and hotel performance

Studies have confirmed that greater dynamism in prices leads to enhanced profitability (e.g., Hormby et al., 2010; Aziz et al., 2011; Cross, 2011; Sweeting, 2012; Bayoumi et al., 2013; Abrate et al., 2019). Sweeting (2012) showed that expected revenue increased by16% using dynamic pricing. Even during a recession time, dynamic pricing can boost revenue (Hormby et al, 2010). Aziz et al. (2011) dynamically established prices for a hotel-chain room each night rather than using a predetermined set of rates; they boosted hotel revenue after setting a price that shows current demand and hotel occupancy levels. Bayoumi et al. (2013) built a different dynamic pricing model algorithm to calculate the optimal price models for recommending hotel prices. They found that the multiplier pricing technique improves revenue compared with fixed pricing by 16%. Cross (2011) found an increased RevPAR of

2.7% one year after enhancing the dynamic optimisation pricing relative to variable pricing for the Intercontinental Hotel Group. Al Shakehsheer et al., (2017) demonstrate that hotels employing dynamic pricing and value-based pricing in conjunction with fenced pricing achieve higher RevPAR than hotels that do not. However, Abrate et al. (2019) showed that hotels do not sufficiently apply dynamic prices, suggesting that further variability may increase performance.

More data and information about the customer lead to a better price adjustment. OP is caused by improvements in information technology (Guadix et al., 2010), such as big data (Wang et al., 2015). This facilitated data in real time. Therefore, OP analyses additional data (e.g., reputation, weather, denials and rejects), which increases price dynamism. In addition, instead of applying predetermined BAR ranges, OP adjusts the prices in real time and allows a better adaptation of the demand to customers' WTP. Therefore, it can boost revenue (Talón-Ballestero et al., 2022).

Moreover, while, in variable pricing the rule of rate fences is necessary to allow customers to categorise themselves into the appropriate rate categories according to their needs, behaviour or WTP, service providers must follow rate fences (Hanks et al., 2002; Kimes and Wirtz, 2003). And some studies have shown its effectiveness (Al Shakehsheer et al., 2017). Other studies point out that restrictions do not allow for real dynamism (Shapiro and Drayer 2014; Talón-Ballestero et al., 2022). In support of the latter theory and with the help of big data, OP avoids restrictions, which reduce the ability to book certain days in a multi-day booking with restrictions; thus, they limit occupancy. Therefore, allows customers to make reservations for several days and increases occupancy.

Regarding the effectiveness of the implementation of the OP, there are sectoral studies, as mentioned above, conducted by Duetto (2019b), such as the one conducted on the Ovolo hotel group, in which the one-year implementation of the OP led to a 4% increase in ADR and RevPar. Similarly, in the case of NH hotels, the OP improved 2017 revenues over the previous year on a RevPAR basis by 8.5%, ADR by 4.9% and OR by 3.4% (Duetto, 2018).

In light of previous studies, according to which higher price dynamism leads to higher profitability, the present study finds that OP pricing allows for greater price dynamism than dynamic variable pricing. Moreover, the effectiveness of OP implementation has already

been demonstrated in practical studies (Duetto, 2018, 2019b). Thus, the first hypothesis of this study is put forward (see figure 1).

H1: Increased dynamism in pricing boosts hotel revenues.

In hotels, some of the most important KPIs measuring profitability and comparing performance are OR, ADR and RevPAR, which have been used in other studies (Enz and Canina, 2011). Researchers have examined how the ADR and OR influence RevPAR (Enz and Canina, 2011; Sainaghi et al., 2019).

Profitability from RM should be measured in terms of the RevPAR mean, and budget calculations should be compared (Zaki, 2022). The relationships between ADR, OR and RevPAR are critical for evaluating a hotel's revenue and productivity and comparing performance (Mauri, 2013).

On the one hand, Abrate et al. (2019) looked into the effect of dynamic price variability on RevPAR considering the OR and ADR. The OR increases significantly with high price variability and is associated with a lower ADR. This has a positive effect on occupancy, resulting in increased revenue (Croes and Semrad, 2012). The OR indicates the hotel's power to use its fixed capacities, managing the seasonality of hotel operation (Koenig and Bischoff, 2003). Removing restrictions, rises in occupancy and real-time data allow for better demand and price adjustment (Talón-Ballestero et al., 2022). Therefore, we propose our next hypothesis.

H1a: The application of OP increases the OR compared to variable pricing.

On the other hand, achieving a right ADR is vital to attaining profitability (Chattopadhyay and Mitra, 2019). In this respect, Noone et al. (2013) discovered that revenue performance was strongest for hotels that price higher than the competition over time. Hotels with a higher ADR have a relatively high RevPAR in both the United States and Europe (Enz and Canina, 2011; Noone et al., 2013). Considering, that with the OP, the adjustment of the price in real-time, without predetermined ranges, allows a better adaptation of the price to the demand, allowing the increase of the ADR, we propose the following hypothesis.

H1b: The application of OP increases the ADR compared to variable pricing.

Considering what has been verified previously, the greater dynamism of the price increases the profitability. The OP better adjusts the price to the client's WTP; thus, the OP could increase ADR and OR. Therefore, the following hypothesis is established: Hence,

H1c: Rises in the KPIs (OR, ADR) increase RevPAR.

In addition, the study controls for confounding variables that can affect a hotel's pricing strategy level. We control for external demand shocks by measuring the effect of local competitors on price (Becerra et al., 2013) to estimate new entries, as well as supply and demand shocks (Porter, 1998), and comparing them. Hotels measure and benchmark the performance of RM policies (Schwartz et al., 2017). This leads to the following hypothesis.

H2: There are statistically significant differences in performance indicators between hotels applying an OP strategy and their competitors.

Figure 1. Empirical framework
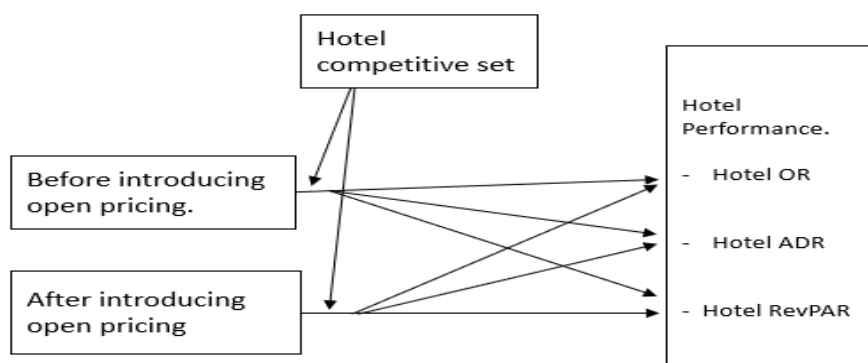
Note: OR: Occupancy rate; ADR: average daily rate; RevPAR: revenue per available room.

Source: author's elaboration.

3   The methodology

The methodology relies on three case studies to observe the effect of OP on business performance and answer 'how' questions, which is appropriate when a phenomenon is poorly understood (Yin, 2003; El Haddad, 2015). It is the preferred approach if a company is viewed as a 'revelatory' case (Yin, 2003). The chosen cases justify the use of case studies based on their revelatory nature. The aim is to examine whether OP improves independent hotels' revenue over the baseline in these three cases.

Although experimental research is still one of the most common methodological approaches in marketing (Viglia and Dolnicar, 2020), its use in business marketing is limited (Viglia, et al., 2021). The method is scantly applied in the tourism field, and most studies examine consumer behaviour (Dyussembayeva, et al., 2022). Fong et al. (2016) call for experimental analyses to be conducted as part of hospitality research, a field in which this is lacking compared to other disciplines, especially in relation to RM (Lopez Mateos, et al., 2020). The current research design will use the single-group before test after test design (Leon and Cuesta, 1993). We will follow the within-subject design of the experiment, which focuses on changes in the same set of samples before and after exposure to the stimuli. Quasi-experimentation is similar to true experimentation; this type of experimental method aims to establish a cause-and-effect relationship between independent and dependent variables. However, randomised experiments fail to control for various threats to validity, leading to the weak generalisability of research relationships and unstable statistical inferences (Cook and Campbell, 1986). The quasi-experimental design allows the use of viable techniques to address these difficulties. Longitudinal experiments are a type of quasi-experiment involving repeated examination over time: the same participant (i.e. a single hotel) is investigated over time to determine whether the dependent variable changes at any point (Viglia et al., 2021).

According to Viglia et al. (2021), this method has maximal external validity. We followed the conditions established in Slack and Draugalis (2001). To ensure external validity, we conducted repeated assessments over time, looking for trends or potential changes in the dependent variable.

The selection of the sample was especially challenging to ensure both internal and external validity. In cooperation with Beonprice (RM systems outsourcing OP), the analysed hotels had to meet the following criteria:

- The hotels should be independent because we wanted to evaluate the impact of OP on this type of hotel, which applies it less frequently.

- The hotels should be midscale hotels located in urban areas within large Spanish tourist cities because urban hotels are the most developed in RM (Talón-Ballestero et al., 2011).

- To control the reactive effects of experimental arrangements (Slack and Draugalis, 2001), the hotels should not be in competition with each other (located in different big cities).

- To prevent selection interactions that involve maturation (Slack and Draugalis, 2001), the hotels should have the same dates in March 2018 to start the implementation.

- To control history and other internal impact on internal validity (Slack and Draugalis, 2001), we held the service context constant. There were no significant changes in the hotels' situation (neither in management nor in any other circumstance) during the study period.

- The hotels should have the same policy before the OP intervention; they used a variable dynamic pricing policy before the implementation of OP.

- To control confounding variables impact, the competitor hotels should not show a significant change in their situation, similar to the OP hotels during the study.

- To avoid the regression threat based on extreme scores, we choose three different hotels with three different levels of performance compared to their competitors.

Thus, the impact of OP application can be measured.

Filtering all the Beonprice data returned 200 hotels, including 25 each in Madrid and Barcelona and approximately 15 in Seville. The final number of hotels meeting the criteria was reduced to three (Table 1). None was mature in terms of RM culture. The hotels analysed only the pickup, did not make a detailed forecast and did not have a very structured decision-making process. Fully evolving the system requires two to six weeks from the end of the 'before' setting to the start of the 'after' setting (Jain and Bowman, 2005). Anonymity was preserved by referring to them as OP hotels.

Table 1 Dataset of hotels implementing open pricing

City	Number of rooms	Management model	Hotel age in years	Competitors	Stars
Madrid	232	Lease	70	58	4
Barcelona	67	Owned	15	44	4

Seville	134	Owned	50	10	4

Source: author's elaboration.

The causality between OP and the results was found by analysing the results before application (first control variable) with those of the following two years (after treatment). Quasi-experimentation was applied as participation was not random (see Viglia and Dolnicar, 2020) to demonstrate what occurred before and after OP implementation. This was done by quantifying the hotel's performance in percentage after applying OP. Our methodology was based on that of Rannou and Melli (2003), who measured hotel performance by determining the differences between the treatment and control groups over two separate periods, comparing RM performance before and after.

Controlling for potentially confounding variables minimises the potential for an alternative explanation for treatment effects and provides more confidence in the effects of OP. The local competition (Barney and Hesterly, 2008) was used as a control variable (Becerra et al., 2013). The OP intervention is not given to the second control group. As a result, if the intervention group experiences the effect but not the control group, then the causal inference is strengthened (Schweizer et al., 2016; Viglia et al., 2021). We controlled for external demand shocks (competition) and consequently confirmed that OP was the main explanation for the change. The results of the competitor hotels that do not use OP application during the same years were compared. The competitors adopted "variable pricing.

3.1   Data collection

A sample of three independent hotels was sufficient to detect an effect size (f) of 0.408 at a power (1-β) of 80 % (0.8) and a partial eta squared of 0.143 at the 0.05 significance level. Three mid-scale independent urban hotels were selected and followed for 36 months (2017, 2018 and 2019). Daily performance was also followed for 1,095 days (approximately three years). The sample size was calculated using G*power software version 3.1.9.6 for Mac OS (Faul et al., 2007). The daily OR, daily ADR and RevPAR are well-accepted operating ratios for examining performance (Enz and Canina, 2011). The number of observations was 1,095. We collected data from Beonprice.

The second step was to control the effect of local competition on pricing performance. We collected daily data for competitor hotels from the same category in the same geographic area as OP hotels for three years (Guerras and Navas, 2007). The data were collected from STR, and each hotel determined its competitive set according to STR guidelines (Enz and Canina, 2015). The hotels in one group had to be relatively homogeneous to enable us to identify differences between their means. The use of this sample is justified because it has the major factors of the main hotel (Enz et al., 2015). In total, 112 four-star hotels were examined and compared with OP hotels. We analysed annual rather than monthly data to reduce any month-specific pricing irregularities that would not be representative of the overall pricing strategy (Ismail et al., 2002). The competitors did not apply OP and adopted variable pricing.

The sample was selected based on the importance of the Spanish hotel sector, a suitable context for conducting this study as it is one of the pillars of the national economy. The sector increased the GDP by 12.4% and sustained 12.9% of employment in 2019. It is characterised by a high level of competition and diversity. Urban midscale hotels in Madrid, Barcelona and Seville were investigated for this study. The Spanish hotel sector is a benchmark in the international hotel industry because of its strong commitment to internationalisation (Gémar et al., 2016). As a result, its global application perspective is greater. The tendency to use dynamic pricing is increasing among four- and five-star hotels (Melis and Piga, 2017).

3.2   Data analysis

SPSS 25 was used for the descriptive statistics and variance analysis tests for the one-way repeated measures analysis and a pairwise comparison of the means, respectively. Data were analysed using Friedman's test, a non-parametric statistical test employed to detect differences across multiple tests. Ortega (2016) evaluated RM performance by estimating different variance analyses. Altin et al. (2017) compared RM performance for various hotels using ANOVA variance analyses.

A skewness-kurtosis test suggested that the variables were not normally distributed (see Table A.1 in the Appendix). The data were thus examined using the Shapiro-Wilk and Kolmogorov-Smirnov tests for univariate normality, where $p > 0.05$ for each of the dependent variables. The results, which defined the different data points for each year and each hotel,

suggested that the variables did not deviate from a normal distribution. Thus, a Friedman's test was applied, and an ANOVA test was then used for the large data and conformity. Table A.1 also shows the median, maximum and minimum values of each variable. Further, we analysed the effect of local competition on pricing performance and on the OR, ADR and RevPAR in the context of comparative behaviour, based on the methodology of Zheng et al. (2016). A t-test was performed to identify any significant difference between the means of OP and competitor hotels.

4   Results

Figure 2 shows the annual and monthly OR changes, demonstrating that the OR increased each year for each hotel. The upper figure shows the variation in monthly performance over the three years. The OR performance in certain months increased above the monthly average, which could be due to specific events. For instance, in May 2019, the OR rose above the monthly average in Madrid because of the UEFA Champions League final. Similarly, in Seville, it increased above the monthly average in April because of the Seville April Fair, and in Barcelona, it grew in March because of the Mobile World Congress and E-show Barcelona, among other events. The lower figure presents the annual mean performance. The annual changes in the OR in Madrid, Barcelona and Seville (Table A.1 in the Appendix) between the groups were measured using Freidman's test, demonstrating that the variance between the means was significantly different between 2017 and 2019, at the 0.05 level, for each hotel. The results show that the OR significantly increased ($p<0.001$) after the first and second years compared with before the introduction of OP. Therefore, we can conclude that not all group means are equal. Specifically, the OR rose in the three hotels after two years of OP implementation by 9%, 12% and 4% in Madrid, Barcelona, and Seville, respectively. Hence, H1a is supported.

Figure 2. Changes in the occupancy rate in Madrid, Seville and Barcelona
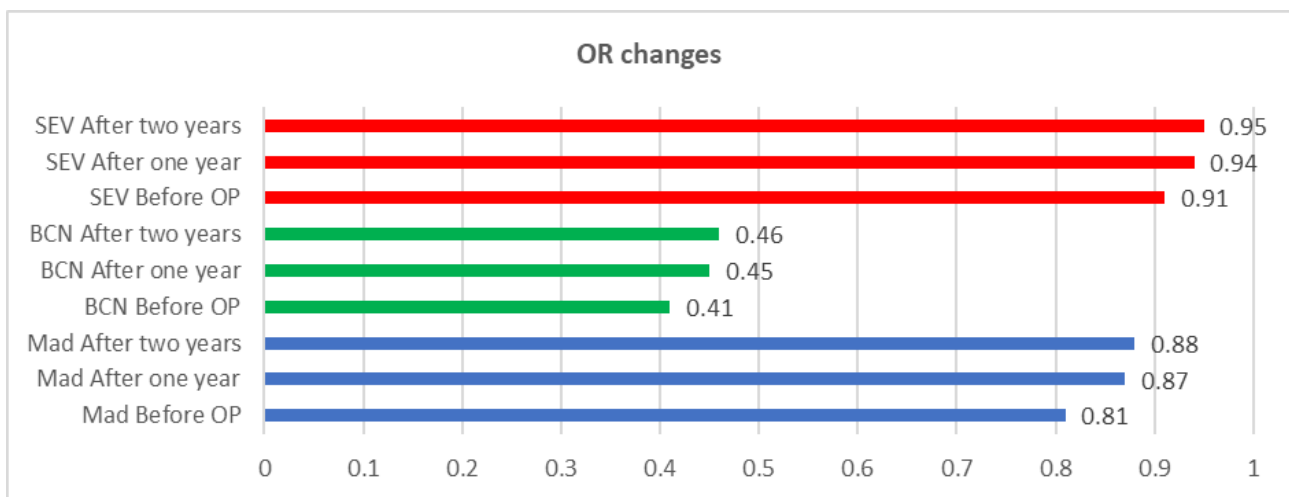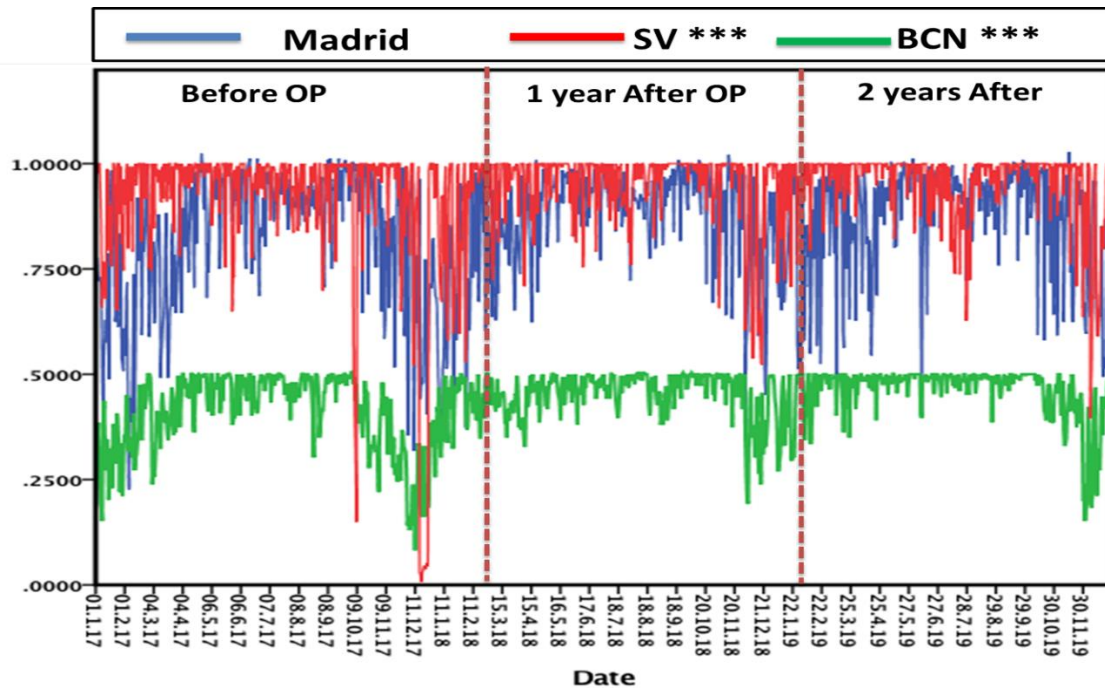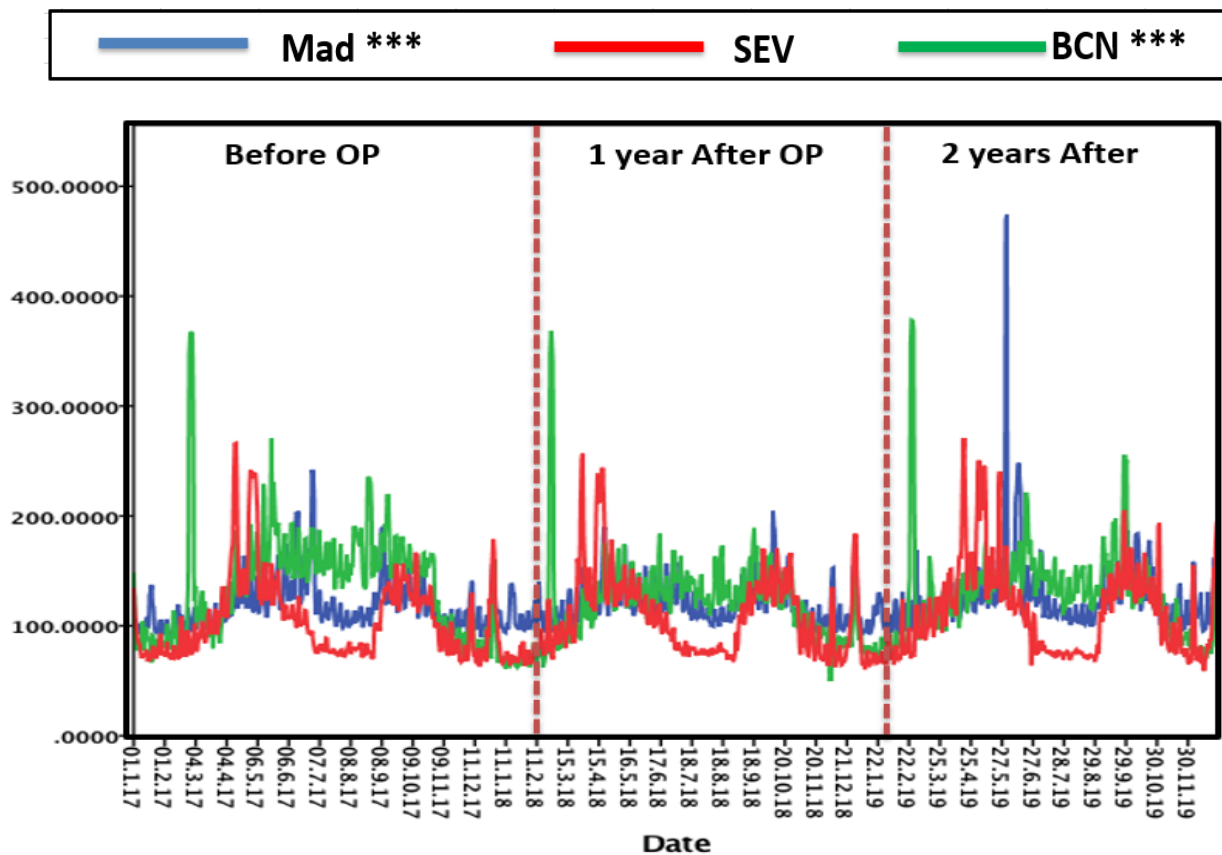
SV: Seville; BCN: Barcelona; Mad: Madrid; OP: open pricing; OR: occupancy rate.

Source: author's elaboration.

Figure 3 shows annual and monthly changes in the ADR, which vary by market. The upper figure represents the range of the monthly performance over the three years. Like the OR, the ADR grew above the monthly average in certain months in some cities because of particular events, as previously explained. The lower figure shows that annual changes in the ADR increased, except in 2018 in Barcelona. As seen in Table A.1 (Appendix), the annual ADR in Madrid, Barcelona and Seville evolved before and after the first and second years of OP implementation ($p<0.001$, statistically significant). The results again allow us to conclude

that not all group medians are equal. After the implementation of OP, the ADR increased by 10% from 2017 to 2019 in Madrid, 14% in Seville and 0.04% in the second year in Barcelona. Therefore, H1b is supported.

Figure 3. Changes in the average daily rate in Madrid, Seville and Barcelona

ADR Changes

Category	Value
SEV After two years	116,14
SEV After one year	105,72
SEV Before OP	101,97
BCN After two years	131,23
BCN After one year	120,13
BCN Before OP	131,19
Mad After two years	129,023
Mad After one year	120,29
Mad Before OP	117,24

(Horizontal axis: 0, 20, 40, 60, 80, 100, 120, 140)
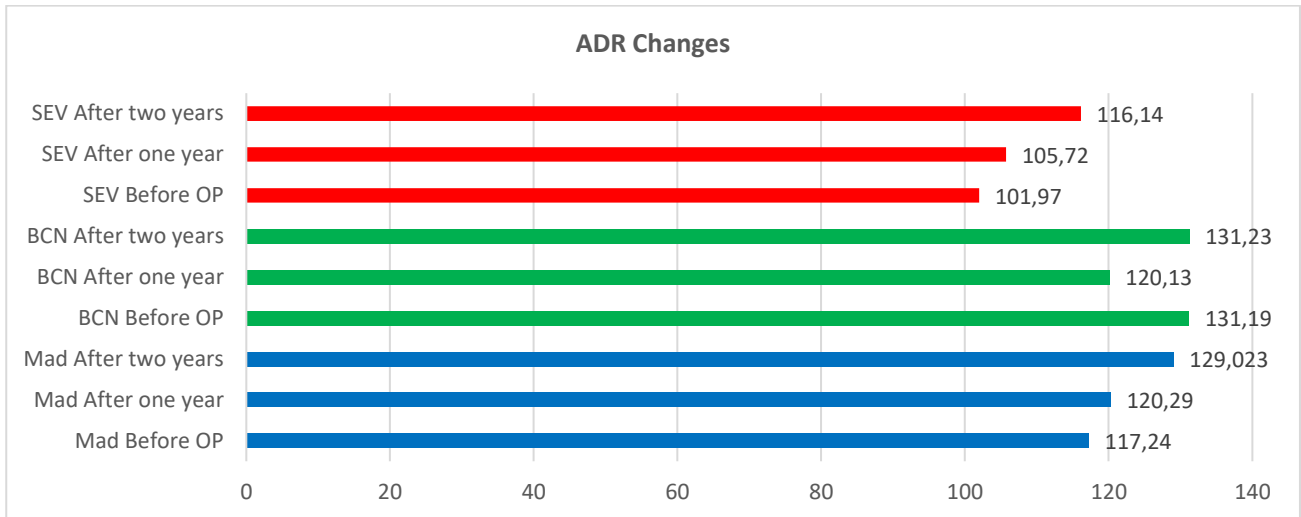
Note: SEV: Seville; BCN: Barcelona; Mad: Madrid OP: open pricing; ADR: average daily rate.
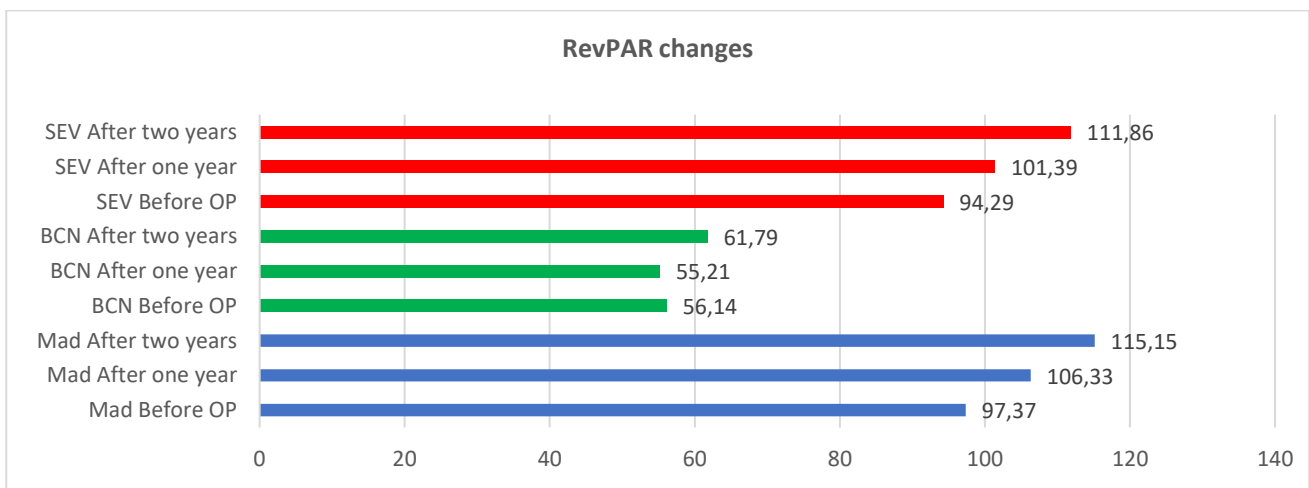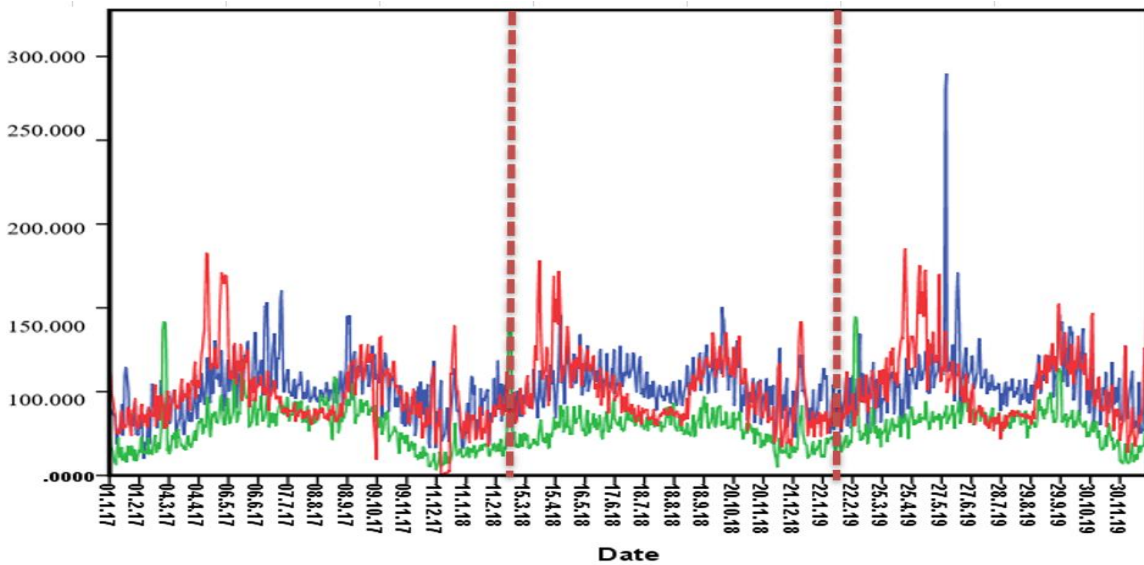
Source: author's elaboration.

Figure 4 illustrates the annual and monthly RevPAR changes in Madrid, Barcelona and Seville before and after the first and second years of OP implementation in the hotels. The upper figure shows high performance in some months, which could be due to a specific event detected by the new system. The lower figure indicates the mean RevPAR. Using Friedman's test and p-value, the results in Table A.1 (Appendix) were found to be statistically significant between the time trends for each hotel. In particular, there was a statistically significant difference between 2017 and 2019: the sample hotels achieved relatively high RevPAR by implementing OP. Hence, OP had a statistically significant effect, increasing the RevPAR for the three hotels, thus supporting H1c. The RevPAR increased by 18%, 10% and 19% in Madrid, Barcelona and Seville, respectively.

The data in all three tables indicate a significant difference in the hotels' OR, ADR and RevPAR over the years ($p<0.001$), rejecting Ho and accepting a significant difference between the units of observation.

Figure 4. Changes in revenue per available room in Madrid, Seville and Barcelona
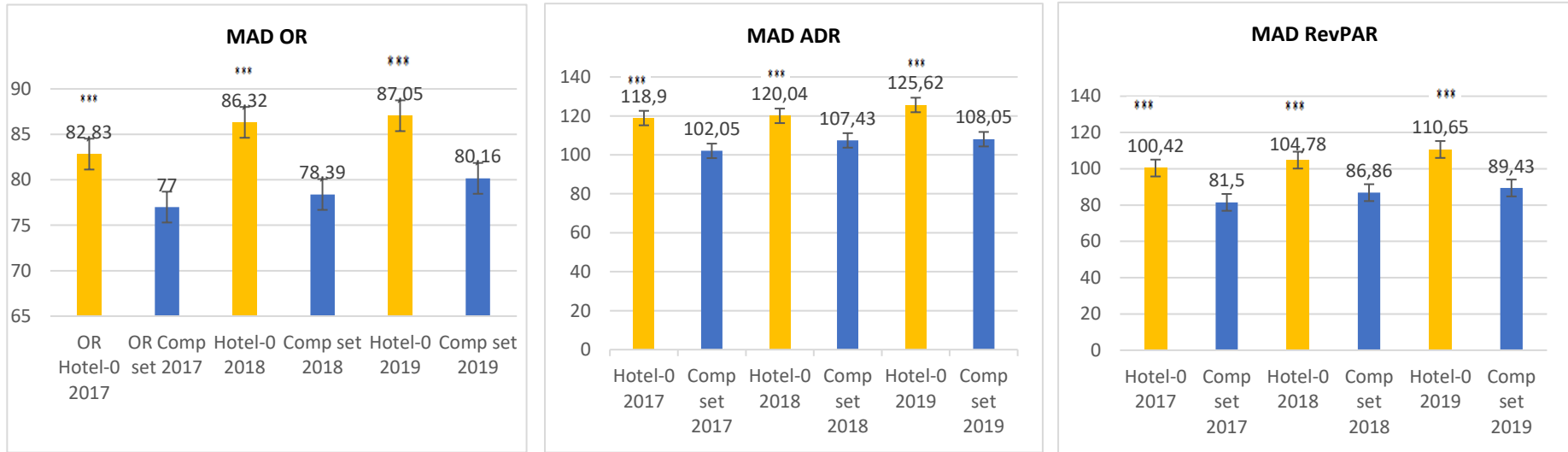
Mad ***   SEV   BCN ***

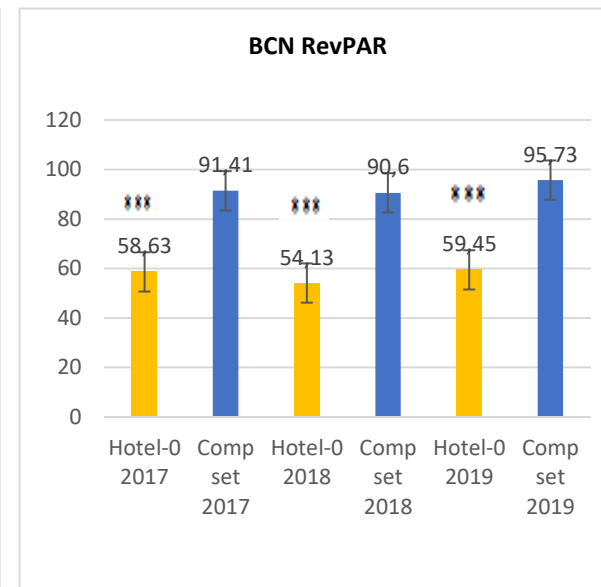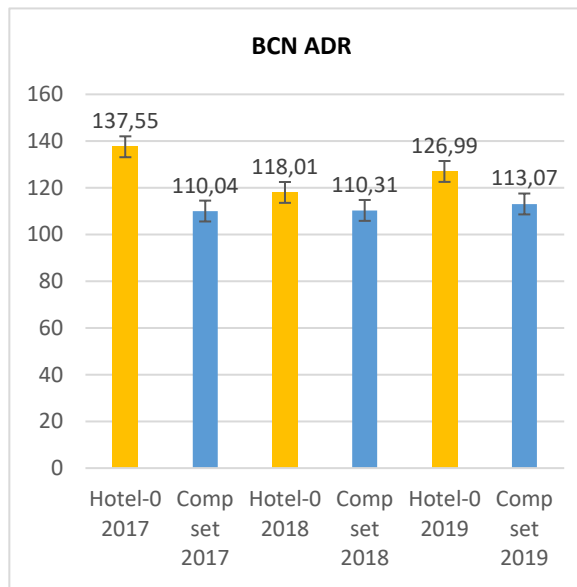Note: SV: Seville; BCN: Barcelona; Mad: Madrid; OP: open pricing; RevPAR: revenue per available room.
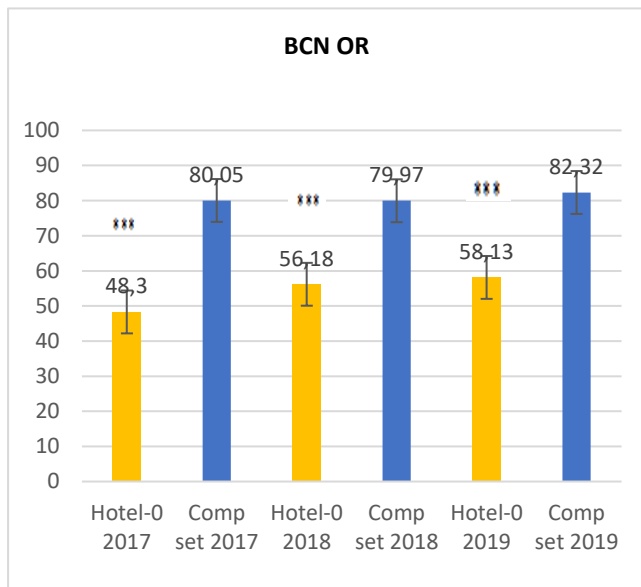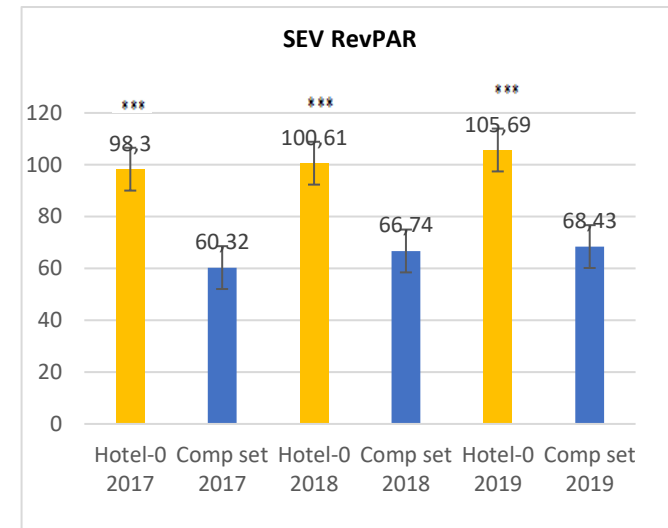
Source: author's elaboration.

Figure 5 illustrates the impact of local competition by comparing the OR, ADR and RevPAR for the OP hotels and competitors from 2017 to 2019. Differences were assessed via an

independent sample t-test at the 0.05 level. The performance of the OP hotels revealed statistically significant differences with the mean of their competitive set in the context of the OR, ADR and RevPAR. The absolute value of the t-test was greater than the critical value samples t-test at the 0.05 significance level; consequently, we rejected the null hypothesis and concluded that the results were statistically significant, confirming the hypothesis. Thus, H2 is supported. Therefore, hotels implementing OP can better adapt to market changes by leveraging price and capacity with greater accuracy. RevPAR variability in OP hotels is driven by ADR and some cases by OR. In Madrid, OP hotel varying its ADR by 10 % between the first and third years and increasing its RevPAR variation by 18 %. In Seville, OP hotel's ADR varied by 14 % from the first to the third year, increasing its RevPAR variation by 19%. Finally, OP hotel in Barcelona's ADR variation increased by 0.04 % from the first to the third year, and the OR increased by 10 %, which translated to a 10 % increase in its RevPAR. In this sense, the explanation is that the Barcelona hotel and the Madrid and Seville hotels in the sample used different strategies to increase RevPAR. For example, in Barcelona, owing to the Catalan crisis of 2017, the strategy used by the selected hotel was to lower prices compared to competitors to increase RevPAR. In contrast, in Madrid and Seville, the strategy was to raise prices, thus boosting RevPAR. Therefore, the idea that the subsequent differences result from the application of OP was reinforced.

Figure 5 Comparison of the difference in hotels' performance between the first and third years (2017–2019)

BCN OR

Hotel-0 2017	48,3 ***
Comp set 2017	80,05
Hotel-0 2018	56,18 ***
Comp set 2018	79,97
Hotel-0 2019	58,13 ***
Comp set 2019	82,32

BCN ADR

Hotel-0 2017	137,55
Comp set 2017	110,04
Hotel-0 2018	118,01
Comp set 2018	110,31
Hotel-0 2019	126,99
Comp set 2019	113,07

BCN RevPAR

Hotel-0 2017	58,63 ***
Comp set 2017	91,41
Hotel-0 2018	54,13 ***
Comp set 2018	90,6
Hotel-0 2019	59,45 ***
Comp set 2019	95,73

SEV OR

	Hotel-0 2017	Comp set 2017	Hotel-0 2018	Comp set 2018	Hotel-0 2019	Comp set 2019
	*** 91,46	75,36	*** 93,99	76,35	*** 94,94	78,78

SEV ADR

	Hotel-0 2017	Comp set 2017	Hotel-0 2018	Comp set 2018	Hotel-0 2019	Comp set 2019
	*** 105,96	76,57	*** 105,67	84,07	*** 109,83	83,9

SEV RevPAR

	Hotel-0 2017	Comp set 2017	Hotel-0 2018	Comp set 2018	Hotel-0 2019	Comp set 2019
	*** 98,3	60,32	*** 100,61	66,74	*** 105,69	68,43

Note: OR: occupancy rate; ADR: average daily rate; RevPAR: revenue per available room;

MAD: Madrid; BCN: Barcelona; SV: Seville.

*** denotes the significance between the time points for each hotel.

Source: author's elaboration.

5. Discussion and conclusions

The integration of big data with pricing strategies has produced infinite pricing points. The sophisticated model of dynamic pricing termed 'OP' by Duetto (Guillet, 2020) can improve hotel performance. However, few experimental studies have been conducted on the effectiveness of this technique, perhaps because of the difficulty of obtaining financial data. Talón-Ballestero et al (2022) called for examining OP impact in hotels. Moreover, Fong et al. (2016) call for experimental analyses to be conducted as part of hospitality research, especially in relation to RM (Lopez Mateos, et al., 2020). This study contributes to solving these issues by exploring the impact of OP in hotel sector. Specifically, it demonstrates the extent to which OP, when applied to RM, improves independent hotels' revenue by raising the OR, ADR and RevPAR.

Table 2. Results of the hypotheses

Hypotheses	Path	Result
H1	Increased dynamism in pricing boosts hotel revenues.	Supported
H1a	The application of OP increases the OR compared to variable pricing.	Supported
H1b	The application of OP increases the ADR compared to variable pricing.	Supported
H1c	Rises in the KPIs (OR, ADR) increase RevPAR.	Supported
H2	There are statistically significant differences in performance indicators between hotels applying an open pricing strategy and their competitors.	Supported

Note: OR: occupancy rate; ADR: average daily rate; RevPAR: revenue per available room.

Source: author's elaboration.

As illustrated in Table 2, the findings support H1, showing that the overall revenue increased significantly after the first and second years compared with 2017. These results confirm both the dynamic pricing theory and the suggestion of Abrate et al. (2019) that greater dynamic price variability raises revenue. In our study, good results were obtained by raising the expected OR, ADR and RevPAR.

These findings are in line with those of Guadix et al. (2010) in that technological advancement by RM leads to a more complex revenue business. Additionally, our findings concur with those of other studies regarding the implementation of dynamic prices after a fixed pricing strategy (Boyd, 1998; Hormby et al., 2010; Aziz et al., 2011; Bayoumi et al., 2013; Al Shakehsheer et al., 2017) or modifying existing dynamic pricing (Cross, 2011; Sweeting, 2012) who find that increased RevPAR is generally attributable to RM, which is mainly applied through dynamic pricing. Talón-Ballestero et al. (2022) asserted that OP has no predetermined prices and can boost revenue over the traditional price ranges.

After two years applying OP in Madrid, Barcelona and Seville, the OR increased by 9%, 12% and 4%, respectively, the ADR by 10%, 0.04% and 14% and the RevPAR by 18%, 10% and 19%. The revenue was higher after the first year and predominantly after the second year, for several reasons. After two years, OP was adopted by all three hotels, allowing the RM team to optimise rates multiple times a day. Furthermore, this allowed the RM team time to think more strategically. Based on big data and the capabilities of the new RM system, the removal of price ranges increased reservations as customers could find a price that they were WTP besides the price setting in real-time. These results are much higher than those reported by the previously mentioned studies. This may be because the performance is reported after two years of implementation instead of one year. However, in the case of independent hotels, these differences in performance may be greater because the before OP the hotels did not apply RM correctly.

Previous studies have reported results after a variable pricing strategy. A professional study by Duetto (2019b) has shown that after one year of OP implementation, Ovolo Hotels reported that the ADR and RevPAR increased by 4%. Likewise, for NH hotels, OP improved the 2017 revenue from the previous year based on the RevPAR by 8.5%, the ADR by 4.9% and the OR by 3.4% (Duetto, 2018). Thus, our findings address the knowledge gap in RM pointed out by Wang et al. (2015), indicating that dynamic pricing should depend on the opportunities offered by big data instead of relying on variable pricing based on historical and predicted demand analysis.

The findings also support H2 as the performance indicators show statistically significant differences between hotels applying an OP strategy and their competitors. In summary, the three OP hotels demonstrated an improved RevPAR after implementing OP. The OP application is better adjusted to the circumstances of the environment. Interestingly, OP hotels applied different strategies of adapting prices to the demand in order to reduce the difference in the competitors' and the OP hotels' RevPARs. Madrid's and Seville's OP hotel prices adapted to increasing demand. They used a qualitative strategy to improve RevPAR. The OP hotels vary the ADR and increase ng the RevPAR variation. In contrast hotel in Barcelona used a quantitative RM. Due to Catalonia's crisis, the performance decreased from October 2017 to 2018 due to the referendum, and the ADR fell by 1.2% across Catalonia and RevPAR by 5.1% in Barcelona (STR, 2019). Occupancy used as a lever or keeping prices without increase. Thus, obtaining higher variations in the RevPAR. The adaptation of the price to the demand aimed to reduce the difference between the OP hotel and the competitors in terms of RevPAR.

A significant conclusion is that the adoption of OP is required in independent hotels and can deliver further benefits. Technology is making RM as accessible to independent hotels as to branded hotels. Hoteliers thus need RM systems that improve their data usage and customer knowledge, leading to better customer segmentation and increases in revenue (Vives and Jacob, 2020). Technology helps revenue managers automate complicated and repetitive tasks to focus on the RM strategy (Duetto, 2019b). The cost of implementing OP should be viewed as a long-term investment. As pricing now relies on big data technology (Millauer and Vellekoop, 2019), OP discrimination is developing in the industry. This challenges the future of price optimisation, which should be based on the value of customers (customer lifetime value) and their WTP (Von Martens and Hilbert, 2011). This approach can form the basis for establishing tailored customised prices (Viglia and Abrate, 2019).

5.1   Theoretical implications

These findings contribute theoretically to the literature on dynamic pricing. The study confirms and extends the literature on dynamic pricing and RM systems by using datasets and daily pricing information regarding three different hotels in different markets. The study

provides the first academic research on the impact of OP on hotel revenues. It delivers to the academy's dynamic pricing concept that is currently being used in business and has only been covered by Talón-Ballestero et al. (2022). It deepens into the OP concept and the structure of the RM system. The study demonstrates its effectiveness using real data from the sector and develops the quasi-experiment methodology for verification and a longitudinal study that is rarely used in hotel research. It demonstrates that OP can boost individual hotel revenue and provides insights into its impact on the hotel sector. It thus opens the door for researchers to understand trends in OP and its utility for raising hotel revenue.

5.2   Practical implications

This study explores new pricing trends and empirically presents their benefits and challenges for revenue managers. It introduces a practical solution to this problem. RM system vendors are building their OP strategy on different parameters. These data differ according to the system, in turn affecting the price setting and productivity of each system. This understanding will benefit practitioners by offering clear insights into how to implement or improve OP in independent hotels. The findings also support individual hotels in changing their traditional views of RM systems. This study presents practitioners with data to delve into OP and RM systems. The new technology applied by RM systems and automated pricing techniques through OP has allowed revenue managers to be more strategic (Duetto, 2019b). Thus, OP should be considered an investment by independent hotels.

5.3   Limitations and avenues for future research

From a methodological standpoint, the use of only three case studies can be considered a limitation, and our conclusions cannot be generalised. The objective of the experiment was to test the relationships in the selected sample but not to generalise the results. The three hotels were selected because they met the quasi-experiment study criteria, and the study was conducted with only three hotels to control the internal validity of the experiment. Although the sample size calculation validates the appropriateness of the use of three hotels, a bigger sample size would be desirable in future investigations. The study would be repeated in other contexts (such as, beach hotels) to test other markets and pursue said generalisation. Additional studies could look into varying room types or other inventory

characteristics and segments to understand the effects of OP in detail. They could also compare the different algorithms applied, as well as hotels that do and do not use OP techniques as they recovered from the COVID-19 pandemic in 2021 and 2022.

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Appendix I. Descriptive statistics

Table A.1 Descriptive statistics for the occupancy rate, average daily rate and revenue per available room of the hotels in Madrid, Barcelona and Seville that implemented open pricing

OR	Madrid			Barcelona			Seville		
	Before open pricing	After one year	After two years	Before open pricing	After one year	After two years	Before open pricing	After one year	After two years
Mean	0.81	0.87	0.88	0.41	0.45	0.46	0.91	0.94	0.95
Median	0.86	0.91	0.93	0.44	0.47	0.49	0.98	0.99	0.99
Variance	0.03	0.01	0.015	0.009	0.003	0.004	0.031	0.008	0.009
SD	0.17	0.11	0.123	0.092	0.058	0.064	0.174	0.09	0.092
Minimum	0.22	0.36	0.41	0.082	0.192	0.151	0.007	0.522	0.395
Maximum	1.02	1.02	1.03	0.507	0.503	0.503	1	1	1
Range	0.8	0.66	0.62	0.425	0.3109	0.351	0.99	0.47	0.6
Interquartile range	0.23	0.13	0.12	0.139	0.068	0.044	0.089	0.067	0.067
Skewness	-1.04	-1.47	-1.52	-1.10	-1.67	-2.83	-3.51	-2.49	-2.66
Kurtosis	0.37	2.003	1.60	0.55	2.82	8.43	13.83	6.46	8.26
Friedman's test	<0.001***			<0.001***			<0.001***		
ANOVA p value	<0.001***			<0.001***			<0.001***		
ANOVA F ratio	28.71			55.143			11.249		
ADR	Madrid			Barcelona			Seville		
	Before open pricing	After one year	After two years	Before open pricing	After one year	After two years	Before open pricing	After one year	After two years
Mean	117.24	120.29	129.023	131.19	120.13	131.23	101.97	105.72	116.14
Median	112.025	116.52	120.74	133.71	120.08	130.86	89.89	98.13	116.14
Variance	520.49	404.843	1394.55	2862.09	1422.14	937.36	1297.04	1350.69	1753.34
SD	22.81	20.12	37.34	53.49	37.71	30.62	36.01	36.75	41.87
Minimum	87.22	92.062	95.06	61.25	49.58	70.29	62.99	60.31	58.86
Maximum	242.09	204.21	473.99	368.37	378.27	255.7	266.29	256.47	270.95
Range	154.88	112.14	378.94	307.12	328.69	185.4	203.29	196.164	212.09
Interquartile range	24.55	24.37	26.98	72.6	44.33	34.019	43.78	51.07	59.18
Skewness	1.98	1.073	5.62	1.51	3.18	0.73	1.88	1.33	1.09
Kurtosis	5.77	1.06	46.33	4.40	19.40	2.31	4.56	2.18	1.19
Friedman's test	<0.001***			<0.001***			<0.001***		
ANOVA p value	<0.001***			<0.001***			<0.001***		

	Madrid			Barcelona			Seville		
ANOVA F ratio	17.548			8.088			12.743		

RevPAR	Madrid Before open pricing	After one year	After two years	Barcelona Before open pricing	After one year	After two years	Seville Before open pricing	After one year	After two years
Mean	97.37	106.33	115.15	56.14	55.21	61.79	94.29	101.39	111.86
Median	97	106.42	111.31	52.61	54.96	63.3	84.5	93.57	107.4
Variance	1092.09	718.96	1713.63	955.04	446.21	351.6	1649.84	1473.4	2017.23
SD	33.05	26.81	41.39	30.9	21.12	18.75	40.61	38.38	44.91
Minimum	19.99	37.14	45.59	6.36	9.55	14.22	0.57	33.71	27.11
Maximum	220.79	200.91	479.73	184.18	189.14	127.85	265.81	256.47	270.95
Range	200.8	163.77	434.13	177.82	179.58	113.63	265.24	222.76	243.84
Interquartile range	41.35	32.57	33.51	43.96	23.5	19.57	43.65	52.53	61.26
Skewness	0.53	0.32	4.35	1.21	2.43	-0.02	1.17	1.03	0.87
Kurtosis	0.87	0.46	34.71	2.75	13.96	1.51	3.06	1.51	0.78
Friedman's test	<0.001***			<0.001***			<0.001***		
ANOVA p value	<0.001***			<0.001***			<0.001***		
ANOVA F ratio	24.838			6.702			16.161		

Note: OR: occupancy rate; ADR: average daily rate; RevPAR: revenue per available room; SD: standard deviation; ANOVA: analysis of variance.