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Identification of Consumer Behavior Based on Price Elasticity: A Case Study of the Prague Market of Accommodation Services

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Received: 26 October 2020; Accepted: 11 November 2020; Published: 13 November 2020

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Abstract: The article deals with customer behavior in the market of accommodation services. The main purpose of this article is to identify tourist behavior using their sensitivity to changes in the price, based on the data from 2011 to 2018. The results can help to understand the booking behaviors of tourists in the long term period, identify specific situations, and to improve the application of revenue management. Using simple log-log regression analysis, the daily performance data of 103 Prague hotels were analyzed, and the coefficient of price elasticity of demand was identified for various timeframes: low and high seasons, summer months, weekends and weekdays, and individual years. The results show that the coefficient of price elasticity of demand is decreasing. In the low season, the low price sensitivity is caused mainly by the high proportion of the non-yieldable leisure group segment, where fixed rates are created for tour operators more than a year in advance. In the high season, Giffen's paradox was identified in 2016 and shows the situation of customers expecting further growth of room rates. The Giffen paradox was identified only on specific dates of the year and was confirmed by year-to-year growth of the Average Daily Rate.

Keywords: price elasticity of demand; consumer behavior; dynamic pricing; hotel demand; Giffen's paradox

1. Introduction

Dynamic pricing, the ability to set the right prices of hotel products at the right time, is one of the main concepts of revenue management that is being currently revisited by researchers [1–4].

Some authors propose the use of fixed pricing can lead to better performance than using dynamic pricing. Gallego and Ryzin [5] describe dynamic pricing possibilities and their comparison with fixed pricing, where fixed pricing delivers better results. This statement is supported by Xia et al. [6], whose focus is mainly on price fairness and the impact of dynamic pricing on the customers' perception of value and the whole organization. Over fixed pricing, dynamic pricing can capture the impact of various factors on price and its variability over time [7]. Sweeting [8] describes the benefits of dynamic pricing that better match the needs of sellers (maximization of revenue and profit) and buyers (need for specific limited product). Sen [9] compares the policies of fixed and dynamic pricing, supporting the benefits of dynamic pricing. The main focus of recent studies is on dynamic pricing.

The concept of dynamic pricing is being used in sectors with variability of demand in time and fixed product capacity. Oskam et al. [10] and Xie et al. [11] investigate the benefits of dynamic pricing within sharing economy platforms, focusing on accommodation services. Airlines, hotels, and other tourism-based organizations are developing new technologies to increase the positive impact of dynamic pricing on their revenues [3]. With these technologies and automated models, hoteliers can update their selling rates based on the changes in supply and demand and make the price more personalized for the customers [12].

The main focus of this study was to measure one of the critical factors influencing dynamic pricing, price elasticity of demand, and to showcase its development over time and in specific periods. This study used unique whole market data, where most other studies were single property-focused [4,13,14] or specific market segment-oriented [15,16]. None of these studies focused on the whole market or the development of specific influencing factors. This study used STR (Smith Travel Research, London, United Kingdom) daily data for the Prague market with a focus on essential KPIs (Key Performance Indicators) like RevPAR (Revenue per Available Room), occupancy rate, and ADR (Average Daily Rate) from 2011 to 2018. Mainly focusing on different times throughout the year and measuring the price elasticity of demand yearly, during weekdays (Sunday–Thursday), during weekends (Friday and Saturday), during July and August (when the aggregate demand for accommodation is the highest throughout the year in the Prague market), and during the low and high seasons. Kocourek et al. [17] estimated that consumer prices in the hotel and restaurant segment in Prague are, on average, 11.7% higher than in the rest of the country.

The goal of this article is to identify customer behavior in the market of accommodation services with the use of their price elasticity coefficient. The goal of the article is directly connected to the following research question:

- What are the changes in customer behavior in the accommodation service market of Prague in different seasons, in connection to price changes of offered products?

Price elasticity of demand is one of the key inputs for optimization processes connected to price setting and revenue management, and the knowledge of this coefficient can support decision making processes in hotels to increase the revenues of businesses.

2. Literature Review

Revenue management (RM) is one of the critical areas of interest in contemporary hotel business research, with a target to sell the right product at an affordable price, at the right time, with the right distribution channel [18–20].

The most critical part of RM is pricing. Price is essential information for customers in the business and leisure segment [21]. There are currently a large number of alternative pricing approaches. Steed and Gu [20] work with four basic methods, namely cost-oriented pricing, market-based pricing, a combination of both, and other best practice-based methods.

Cost-oriented valuation represents an example of €1 for €1000, or Hubart's formula [22]. Pellinen [23] and O'Neill [24] identify these methods as inadequate and recommend their combination with other, more dynamic methods. Market-oriented pricing is highly influenced by competition [25], customers and their previous experiences [26], and applicable technologies. O'Connor [27] focuses on the impact of online distribution and customer expectations. The expected lower distribution costs, competition selection, and previous online purchasing experiences give customers the feeling that online prices may be lower than on other distribution channels.

Combined approaches include the quadratic model, which is based on the identification of fixed and variable costs, expected demand, and price elasticity (the author is not concerned with its determination but only with estimation). Tung et al. [28] propose a six-step pricing process based on market prices, identified competitors, comparison of the hotel with its competitors, price limits and their creation, and segmentation of customers. Best-practice pricing is based on the identification of pricing processes for selected hotels and their subsequent synthesis or modification, according to the specific hotel [29].

Price variability also plays an important role. The hedonic valuation method works primarily with different characteristics of accommodation facilities [4]. Melis and Piga [3] showed the connection between the hotel characteristics (mainly the class, organization, culture, and design) and the application of dynamic revenue management strategies, using the observation of online rates for Mediterranean hotels on the Online Travel Agents website. Latinopoulos [30] used the semi-parametric geographically weighted regression model to assess the effect of location and room characteristics on pricing strategy, where the sea view appearance (identified for 559 hotel rooms in Halkidiki, Greece) had a positive effect on the room rate. The same results were confirmed in the study of Soler and Gemar [31], who focused on the geographically weighted regression (GWR).

Excluding the geographical location of the accommodation facility, the main characteristics include the precise location within the destination, [32,33], the class of the accommodation facility [34,35], room types, and other attractions near to the hotel [7].

There are more factors that directly influence the pricing strategy of hotels, connected mainly to their characteristics. The study of Balaguer and Pernías [36] focused on competitiveness in the local area and, based on the daily rates comparison, the findings showed that mainly the hotels that offer the same quality of product do affect the price of the hotel. Aquiló et al. [35] used the same approach to analyze the offer of tour operators and their hedonic characteristics.

Abrate and Viglia [34] also showed the growing importance of online reputation as one of the most important decision-making factors slowly substituting the official star rating (class) of the hotels.

Vives et al. [4] describe three fundamental factors of hotel price variability, namely seasonality, date of reservation, and type of reservation (which is closely connected to restrictions and different types of prices). In terms of seasonality, prices are differentiated according to low and high seasons, where in high season, prices are higher, and in low, price discounts or other benefits are applied. This approach is used for tours [37] and air ticket sales [38] as well. The seasonality of demand is influenced by institutional factors such as school holidays, public holidays, or other events [39,40]. Pereira [40] also used all the events and variables to create a trigonometric model that can also be used for forecasting hotel demand, where moving events need to be taken into account even though they cannot be directly implemented within the model due to their nature of moving dates or random occurrence. Coenders et al. [39] used the information about events as a latent variable within their latent growth curve model. The authors also pointed out the need for the use of hedonic hotel characteristics.

Different prices of the same products can also be identified at different times before arrival [41]. Similarly, the combined effect of seasonality and the dates of the reservations can be observed [42]. In addition to time, RM also focuses on the different needs and characteristics of customers, or customer segments, which are reflected in particular types of offers and restrictions [43]. Furthermore, price incentives, discounts, or the use of other restrictions allow revenue managers to find the optimal combination of the number of rooms sold and their selling prices [44].

Sales of the same product at different prices are associated with customer segmentation [18]. One of the basic approaches in customer segmentation is to take into account the time horizon of making a reservation [25,45]. Chalupa and Petricek [45] used the time variable to describe the pricing strategy of the selected hotel in the days before arrival, where the observed hotel used last-minute discounting. This approach was compared with the revenue management strategies proposed by other authors within this field and the authors proposed a different orientation of the pricing strategy (the strategy of increasing room rates). Schütze [25] examined the booking horizon based on the freely available data on the HRS.com portal, where hoteliers increase their rates over time or use the discounting strategy when the occupancy level at the property is inadequate. Segmentation alone may contribute to an increase in overall sales [46].

Analysis and subsequent modeling of demand are based on the identification of changes in the demanded quantity as the sales price change, as well as changes in customer behavior. When determining the price elasticity of demand, it is necessary to take into account a large number of factors that influence customer decisions. In addition to the price itself, the customer is also influenced by the aforementioned non-price factors, such as seasonality, day of the week, time before arrival [14], and personal characteristics of the customer [47].

The price elasticity of demand thus has a direct impact on the price of products sold, as well as on the performance of accommodation facilities [48]. The basic models used in publications focusing on revenue management in the hotel industry include (1) linear and non-linear demand function [49], (2) logistic regression [36], and (3) multiple logistic regression [50,51]. All these models are based on dynamic product valuation, not only for individual customer segments but also for the given occupancy of the accommodation facility and time horizon [2,52].

Measuring the price elasticity of demand alone is not always easy, and in the course of price optimization, it is necessary to count a change (fluctuation) of its values [53,54]. Schwartz [55] points out that customers book their stay well in advance to respond to price changes more than last-minute bookers. Roberts [56] uses the measurement of price elasticity of demand for price optimization within revenue management, focusing on individual customer segments. However, there seems to be a problem in measuring the elasticity of realized demand, that is, customers paying for a given service, not potential demand (i.e., customers who are willing to purchase the service).

Tran [57] works with a model of demand for luxury hotels in the United States of America, that takes into count the level of income for the selected source country, the average daily price per day, and also the exchange rate. The resulting values of price elasticity ranged between −0.03 (in the long run) and −0.02 (in the short run). Hiemstra et al. [58] measured the elasticity of demand for accommodation facilities of the lowest price category (−0.35) and the higher price category (−0.57). Canina et al. [15] focused on the price elasticity of demand for accommodation, ranging from “economy” to “upper upscale” (this structure is taken over from STR Global). Their results show that elasticity is decreasing from the growing category of accommodation facilities (for luxury accommodation facilities, the elasticity is marginally close to zero). Damonte et al. [59] focused on the measurement of price elasticity and its comparison between selected regions of the US in low and high seasons. The measured values for Columbian County ranged between −0.8 and −1.8. For Charleston County, they were between −0.1 and −0.3. Rosselló et al. [60] examined aggregate demand for accommodation services in Germany (−0.84 in elasticity), Great Britain (−0.98), France (−4.18,) and the Netherlands (−0.51).

Many of the available studies focus on aggregate demand within a selected market. Measurements of this elasticity for individual establishments occur only sporadically. In practically oriented studies, for example, Hormby et al. [61] used the measurement of price elasticity of demand to determine optimal prices for individual customer segments of a selected hotel in the Marriott International hotel group. The segmentation focused on the booking horizon, group size, and season [14]. Bayoumi et al. [13] used price elasticity as one of the multipliers in optimizing the revenue management process at the Plaza Hotel in order to maximize revenue from sold accommodation services. It used in-house data and a probit model to estimate price elasticity. The resulting elasticity was negative (−0.4). Aziz et al. [62] used price elasticity in the optimization process to determine the selling price. Price elasticity itself was only estimated using a linear model.

3. Materials and Methods

The paper focuses on the issue of determining the price elasticity of demand in a selected market as a critical indicator for further management of prices and sales. A unique sample of data, covering the period from 2011 to 2018, was used to obtain the appropriate outputs for the article. The data were obtained through the STR Share Center platforms, which are the academic and research-oriented modules of the Smith Travel Research benchmarking program. The data covered 103 accommodation facilities in Prague and were available daily. The whole process of data collection was done through client login into the STR benchmarking tool, where the participating hotels submitted their performance data on a daily basis and these data are used to identify the whole market characteristics (ADR, Occupancy Rate, RevPAR, Supply, Demand, and Census and Sample %), as well for benchmarking the predefined competition set. The dataset used is based on the data from 103 accommodation facilities and their total supply of 14,263 rooms, which represents 40.2% of the market supply in the selected destination of Prague. These hotels were categorized into Midscale (42 hotels) and Upscale (45) classes; the rest of the participating hotels were in Luxury (8) and Economy (8) classes. This data represents excessive information about the whole market. The data were aggregated into one dataset based on price, related quantity demanded, RevPAR, occupancy, and quantity supplied. One of the key inputs for the whole analysis was the coefficient of price elasticity of demand.

There are several approaches to measuring price elasticity that have been described in the previous section of this paper. For this article, however, the log-log regression analysis method in the ordinary least squares (OLS) model was used. The theoretical regression function was determined in this model, which has the following form:

$$\log Q_i = \beta_0 + \beta_1 \times \log P_i + \varepsilon_i \tag{1}$$

where Q_i represents the quantity demanded, and P_i is the average price for the given quantity demanded. The values of β_0 and β_1 are parameters of the theoretical regression function, and ε represents a random error. It follows from the theoretical regression function mentioned above that the demand is a function of its price. Furthermore, an empirical regression function was estimated, which was used throughout the model. It has the following form:

$$\log Q_i = b_0 + b_1 \times \log P_i + e_i \tag{2}$$

where the estimates of β_0 and β_1 are b_0 and b_1. The model is designed under the following condition (3):

$$\sum_{i=1}^{n} {e_i}^2 = \sum_{i=1}^{n} (\log Q_i - b_0 - b_1 \log P_i)^2 \ldots \min \tag{3}$$

Thus, we were looking for an extreme function using partial derivatives, whose formula can be given in the following form:

$$A = \sum_{i=1}^{n} (\log Q_i - b_0 - b_1 \times \log P_i)^2 \tag{4}$$

$$\frac{\partial A}{\partial b_0} = 2\sum_{i=1}^{n} (\log Q_i - b_0 - b_1 \times \log P_{1i}) \times (-1) = 0 \tag{5}$$

$$\frac{\partial A}{\partial b_1} = 2\sum_{i=1}^{n} (\log Q_i - b_0 - b_1 \times \log P_{1i}) \times (-x_i) = 0 \tag{6}$$

The following approaches (sample covariance and variance) were used to estimate parameters b_0 and b_1:

$$b_0 = \overline{\log Q} - b_1 \overline{\log P} \tag{7}$$

$$b_1 = \frac{\frac{1}{n-1} \sum\limits_{i=1}^{n} (\log P_i - \overline{\log P}) \times (\log Q_i - \overline{\log Q})}{\frac{1}{n-1} \sum\limits_{i=1}^{n} (\log P_i - \overline{\log P})^2} \tag{8}$$

From the formulas mentioned above, primarily (6) and (8), we can determine the coefficient of price elasticity as the parameter b_1 (b_1 = E_{pd}). Although the goal of this regression analysis was just an estimate of one of the parameters that determine price elasticity, we focused on the overall output, mainly to test the robustness and reliability of the model. Testing of the regression parameters of the model was carried out using the t-test, where both parameters showed that the variable affects the explained variable and thus, that

$$|t| \geq t_{1-\alpha}(n-k-1) \text{ at the significance level of } \alpha = 0.95 \quad (9)$$

The quality of the regression model was assessed using a determination coefficient, which was determined as:

$$\frac{SSE}{SST} = R^2 \quad (10)$$

where SSE represents the sum of squares and SST represents the total sum of squares. Based on the calculations made, it is necessary to state that the values of the coefficient of determination for all calculated regression functions were higher than 0.8, with an average value of 0.8776. The last test was considered as the significance test of the model for which the classical F-test, based on the coefficient of determination, was chosen. Similarly to the performed regression parameter test, the significance level $\alpha = 0.95$ was chosen here. The results of the performed F-tests confirmed the statistical significance of the model and therefore,

$$F \geq F_{1-\alpha}(k, n-k-1) \quad (11)$$

where F is defined as

$$F = \frac{R^2}{1-R^2} \times \frac{n-k-1}{k} \quad (12)$$

where k represents the number of regression parameters. Due to the large sample of data collected, it was advisable to adjust the data to provide relevant results. The data was adjusted for most calculations; the data was not only adjusted for low season and high season. Other values have been edited already. One way to modify the data is to clean it for extremes, such as with the Grubbs test. These statistical elements are useful, especially when we do not know more about the statistical file (we know only its distribution). However, since we know the analyzed market, this data was adjusted based on a different logic. The data adjustment was based on the assumption that with extremely high or shallow added value (profitability) of the service sold by traditional collective accommodation establishments, price decisions are influenced by several factors other than the demanded quantity. It is the same decision-making logic of a company as described for that of a company in a duopoly or cartel [63,64]. For this purpose, the RevPAR (Revenue per Available Room) was calculated based on the values obtained for each day, which was determined as

$$\text{RevPAR} = Occ \times ADR \quad (13)$$

where Occ represents the average daily occupancy and ADR (Average Daily Rate) is the average daily price. In order to be able to make the final adjustment with the above mentioned extreme values, it was appropriate to know the exact distribution function of the variable (in our case, RevPAR). In order to correctly estimate the course of this distribution function, an extension to the MS Excel software was used, specifically, CrystalBall (release 11.1.2.4.850, 64-bit). This software was used to estimate the best distribution of a random variable. Normal distribution was always recommended for all single years. To adjust for high and low values, only those RevPAR values that were higher than the 10th percentile and less than the 90th percentile were selected. The above-described adjustments were made for each year, and consequently, only data that reached the RevPAR between the set percentiles were used. These values better reflect the real situation of the market.

4. Results

Using a regression model, several measurements were made to obtain price elasticity coefficients for different periods. An example of the regression function for the whole of 2011 may be the following equation:

$$\log Q_{2011} = 5.280155 - 0.48485 \times \log P_{2011} + e \quad (14)$$

Using the method mentioned above, it was possible to identify the values of price elasticity of demand in individual years as well as in the selected periods defined in the previous part of the article. Individual periods reflect the specifics of the hotel sector and Prague as a destination. The elasticity measurement is based on the market data from STR. Price elasticity was measured in:

1. year-round horizon,
2. during weekends (in the hotel sector, these include Friday and Saturday nights),
3. during working days (the remaining days, Sunday to Thursday),
4. during July and August (months with the highest occupancy and the highest demand from international and local tourists),
5. during the high season,
6. during the low season.

Vives et al. [4] describe the same distribution of days of the week between weekdays and weekends. However, this study provides a unique insight into the seasonality of demand. Most studies, and many experts, connect high season primarily with high occupancy rates. [14,40,59]. However, this study took into account the maximization of sales (i.e., quantity) as well as the sales price (measured by ADR). Therefore, the high and low seasons were identified based on RevPAR, which reflects both the sales price and occupancy of the hotels. Figure 1 describes the values of the coefficient of price elasticity of demand from 2011 to 2018. This section may be divided by subheadings. It provides a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

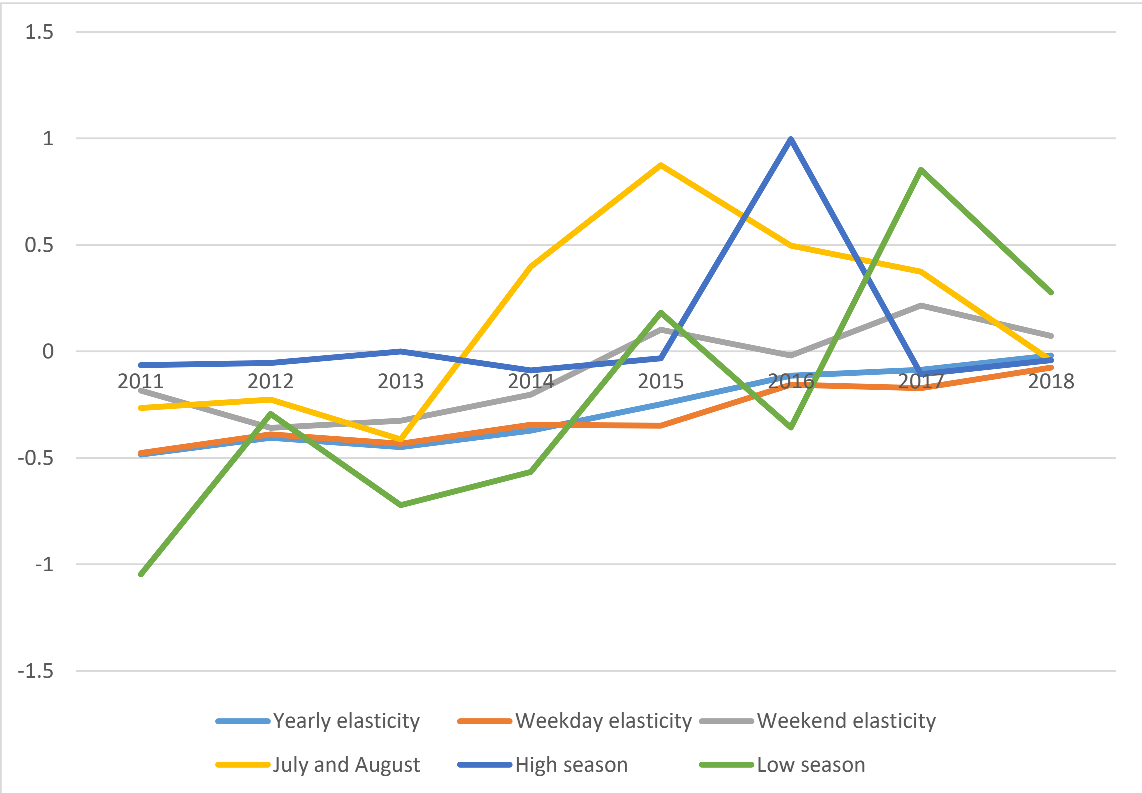

Figure 1. Price elasticity of demand in Prague (between 2011 and 2018), Source: own elaboration.

The general price elasticity of demand in the whole market varied between −0.485 and −0.02 in individual years. These values point to the price inelasticity of demand and fully reflect the findings of other authors [59,60,65,66]. The percentage increases in prices result in a much smaller drop in demand, meaning hoteliers can increase their selling rates more dynamically. A similar development was also reflected in the working days.

During the high season, the price elasticity of demand coefficients varied between −0.107 and −0.0001. The exception was the year 2016, in which the value of 0.997 was measured. Positive values of price elasticity of demand point to an increase in demanded quantity as sales prices rise. This phenomenon can be explained, for example, by the Giffen paradox or the Veblen effect. Heffetz [65] describes the Veblen effect as a situation where a high purchase price by the consumer increases his or her social status. Sometimes this is also described as the effect of snobbish consumption. Konovalova and Vidischeva [67] also reached similar results.

The price demand elasticity also remained positive in the following periods. Table 1 shows the individual values and their development over selected years.

Table 1. Price elasticity of demand in different timeframes.

	2011	2012	2013	2014	2015	2016	2017	2018
Yearly elasticity	−0.485	−0.406	−0.449	−0.372	−0.248	−0.114	−0.086	−0.02
Weekday elasticity	−0.477	−0.39	−0.433	−0.345	−0.349	−0.157	−0.172	−0.076
Weekend elasticity	−0.184	−0.359	−0.325	−0.203	0.102	−0.019	0.215	0.072
July and August	−0.266	−0.227	−0.413	0.397	0.874	0.497	0.374	−0.043
High season	−0.064	−0.054	−0.001	−0.09	−0.033	0.997	−0.107	−0.042
Low season	−1.047	−0.293	−0.722	−0.566	0.182	−0.358	0.852	0.276

Source: Own elaboration.

Based on the presented data, the price inelastic demand can be identified in the long term as the yearly coefficient continuously approaches zero from 2011 to 2018. The most significant value changes can be identified mainly in the low and high seasons and during summer months. In the low season, the significant growth and volatility of the coefficient of price elasticity of demand were identified, as well as the Giffen paradox in 2015, 2017, and 2018. These changes in customer behavior lead to the insensitivity of customers over price changes. As the research shows, during the high season, customers do expect further growth of selling rates, which leads to an increase in demand. The particular situation can be identified during the summer months, where the demand is inelastic. This might be caused by a significant proportion of tour operator bookings, where conditions are created more than a year before arrival. The rates are specified in contracts and hoteliers can use dynamic pricing only for the FIT segment (Frequent Individual Travelers,) which represents only a minor part of the total occupation of hotels.

5. Discussion

Price elasticity of demand can be also related to other types of elasticities and can be compared to other studies. Fleissig [68] says that accommodation service is elastic from the expenditure point of view. It means that accommodation in some periods can be a so-called "luxury good". In the case of increasing consumer income, the number of rooms sold (quantity demand) grows even faster. This finding can help to understand more deeply the behavior of the customers.

Similar results about price elasticity can be also found in the study of Mardsen and Sibly [69] from the year 2017. The authors focus on the increasing elasticity during the winter and decreasing elasticity with increasing quality of the service provided. Those results show a similar finding as our study but from the other point of view. If we compare the findings, we can say that consumers are able to pay a higher price only in the case of other inputs exhibited (in this case, quality).

A relatively large number of factors influence the development of measured price elasticities. Canina et al. [15] point out the effect of the quality of services provided, with the increasing class of accommodation facilities, and the price elasticity of demand for these service decreases. Looking at the source data, it is clear that the main subjects sharing daily data on their performance are mostly four-star or five-star hotels (interpreted according to the STR methodology, which uses a different classification of hotels into classes).

Vives et al. [69,70] point out the need for market segmentation and customer behavior descriptions. They differentiated yieldable and non-yieldable segments according to their responses to price changes over time, as well as other revenues associated with them. Table 2 shows the representation of the main three customer groups in the total average market occupancy. The Group and Contract segments belong to the non-yieldable group. It is therefore not possible to count on an increase in TRevPAR (Total Revenue per Available Room), nor is it possible to count on a price change in the short term. Pricing is determined well ahead of time and data may be distorted.

Table 2. Occupancy in different segments in Prague. Source: own elaboration based on the STR Segmentation Data.

Year	Occupancy (%)			
	Transient	Group	Contract	Total
2011	29.8	30.0	6.8	66.6
2012	31.1	31.7	5.7	68.5
2013	35.0	29.9	4.8	69.6
2014	36.8	28.6	5.2	70.6
2015	41.3	28.6	5.1	75.1
2016	41.3	31.2	4.7	77.2
2017	42.4	33.0	4.7	80.1
2018	41.3	33.4	4.1	78.8

However, the division into three primary segments is not entirely appropriate. The actual behavior of customers on individual distribution channels varies considerably and is very dynamic over time. Targeting correctly, choosing a distribution path, and indirectly choosing target customers are other critical variables that have a direct impact on customer behavior [70,71]. A large part of these studies focuses on the transient segment [4,66], that is, mostly online individual travelers who fully reflect the set prices of sold capacities. Other segments are entirely neglected, thus distorting the overall view of revenue management. As mentioned by Dolasinski et al. [71], the appropriate combination of individual segments leads to the maximization of revenues from accommodation services.

From the segmentation point of view, the time of booking is also essential because there is a relationship between lead time and accommodation prices, where the highest retail prices are reached long before arrival, while the lowest are reached at the last minute. However, this application is only limited to the transient segment, the segment here without a predetermined contract. Another approach to the problem of segmentation describes that accommodation establishment, length of stay, and season are also important factors influencing the set of segments [72].

Another factor influencing price demand elasticity is the total demand for accommodation services in Prague, which grew from 14,443,143 to 18,249,084 bookings between 2012 and 2018. In specific terms, higher demand caused the rate to increase. Demand growth can be used as well to present Giffen's Paradox (still increasing accessibility of accommodation services and traveling) or Veblen's Effect (Prague is commonly selected as not only the final destination but also a transit destination during European tours). Giffen's paradox problem can also present the result that tourism products following people-focused and ecosystem-focused tourism development will show a positive correlation with Giffen's paradox [73].

As presented in the previous section, the Giffen paradox was identified in several periods. The customers strategically make their decisions at specific times before arrival. Masiero, Viglia, and Nieto-Garcia [74] showed that customers make several reservations based on their preferences and their final decisions are postponed based on cancellation policies; the "Book and Search" behavior is identified. Within the period, they reevaluate their decision and choose the best-requested offer, while taking into account the future development of the market. When the future growth of the room rates is identified, they make their final decision sooner and keep their reservation [75]. The time factor is crucial for customers when they are making their decisions.

Another approach to Giffen's paradox shows a so-called counter-example of this issue. The result of this theory is primarily related to substitution effects and shows that poverty seems to be less influential than in the traditional Giffen paradox mentioned. We can assume that this consequence can be also applied in our case, due to the quality standards of selected hotels [76]. The behavior within this period is highly influenced by the price information of hoteliers and their competitors. Competitive environment and leader and follower strategies are applied, and the final room rate converges to rate parity in the market [77].

The combination of all these factors leads to situations where the customer is becoming less and less price-sensitive and waiting for incentives from hoteliers [74,77].

Price elasticity of demand is one of the most important inputs to revenue management decisions in general. Moreover, revenue management can be related to other factors that help to sustain tourism. Ko and Song [78] mention minimizing total investment costs as important inputs to their revenue management model that optimizes the price. This study shows a different approach, but the problem of revenue is actually hidden in the factor of costs. If consumers are price inelastic, there can be a trade-off for paying more to cover the additional cost of sustainability incentives, for example [79]. The Segarra-Ona et al. [80] study mentions that there can be a positive impact on hotel revenue in the case of having Environmental Certification. This can also be a question for future research because having an additional cost for hotels means changing the prices.

6. Conclusions

Dynamic pricing represents a flexible, data-based approach to pricing within the field of revenue management. The presented study shows how to measure one of the critical characteristics of customer behavior: price demand elasticity. Supported by both microeconomics theory and marketing fundamentals, price demand elasticity is still considered to be a key to understanding customer behavior. Most of the currently published studies focus on a static view of price elasticity. Its values are presented for the selected interval, and the authors do not present its development.

The uniqueness of this study lays within the measurement of price demand elasticity during weekends and weekdays, high and low seasons based on the RevPAR values, July and August (the highest number of arrivals on the market), and yearly. The created log-log linear model showed great reliable results that were consistent with the current knowledge presented in previous studies. Another critical finding is connected with the results of price demand elasticity in specific periods, where the elasticity results were positive. This was mainly caused by a lack of market segmentation in the preparation phase, where the study focused on aggregate market data that did not reflect the different developments of significant market segments in the selected period, as well as the continuous development of the Prague market.

The positive value of the coefficient of price elasticity of demand in 2016 (the Giffen paradox) describes customer behavior where the demand grows with the growth of the price. This effect can lead to customer speculation about the future growth of the room rates, which leads to changes in demand; in the short run, the law of diminishing demand is broken. A more in-depth focus on the situation in 2016 shows that the Giffen paradox leads to significant Average Daily Rate growth. This situation was identified only in specific periods during the year (May, September, and the end of the year). The reasoning for such significant price growth and changes in customer behavior should be further examined in future research.

One of the limits of the presented issue can be found in the methodological approach. As mentioned before, other researchers use other approaches to measure price elasticity. We can find multiple regression as one of the approaches [50,51], which uses more variables to determine price elasticity and describe demand. On the other hand, our study focused on the whole market and not on the specific company only. Another limit that has to be mentioned is the validity of the dataset. The input data are based on the information from several hotels and several revenue managers (or other employees) and may be distorted—in means of completeness or correctness. This limitation is typical for studies focused on market data and is hard to overcome. The last limit that can be mentioned is the width of the study. This issue is focused on the market for accommodation services in Prague—this market can be specific and it could be hard to compare with other markets. Further studies should also focus more on market segmentation and measure price demand elasticity for individual segments (transient, group, and corporate) or on single property characteristics with detailed segmentation (based on distribution channel, general market segment membership, demographics, and more).

The output from this article should help in understanding consumer behavior in the market of accommodation services and could be the basis for models that use price optimization approaches to increase the revenue of firms.

Author Contributions: Conceptualization, M.P. and S.C.; methodology, M.P.; software, M.P. and S.C.; validation, M.P., S.C. and K.C.; formal analysis, M.P.; investigation, S.C. and K.C.; resources, K.C.; data curation, M.P. and S.C.; writing—original draft preparation, M.P. and S.C.; writing—review and editing, M.P. and S.C.; visualization, S.C.; supervision, M.P. and K.C.; project administration, M.P., S.C. and K.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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