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The Price Determinants of Airbnb in Rotterdam

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1. Introduction

1.1. Airbnb

Over the last decade, the worldwide economic importance of the sharing economy has grown rapidly (Sundararajan, 2016). Platforms for peer-to-peer accommodations sharing have experienced strong growth within the sharing economy landscape (PWC, 2015). Peer-to-peer platforms allow users to offer products and services while the platform operator manages and maintains the market place (Bostman and Rogers, 2011). Airbnb has pioneered the use of this business model to connect people who want to offer their homes, or parts of them, for rent to tourists and others in need of short-term accommodation (Ikkala and Lampinen, 2014b; Zervas et al., 2016; Wang and Nicolau, 2017a).

The Airbnb concept was created by two university graduates who converted their home into an ''Air Bed & Breakfast'' by offering overnight stays on air mattresses during a San Francisco conference in 2007 (Oskam, 2016; Gebbia, 2016). The company that started with three air mattresses and broke roommates, now offers luxurious lofts, penthouse suites and properties for more than 20 people (Carson, 2016; Oskam, 2016). They converted the ''inviting strangers to your personal place'' concept into a profitable business model. Since launching in 2008, the business model has seen rapid growth: it has become one of the largest single tourism accommodation distribution platforms in the world, with 3.000.000 listings and 200.000.000 guests in 65.000 cities and more than 191 countries worldwide (Gibbs et al., 2017; Airbnb, 2017a; Teubner et al., 2017). Airbnb has become both a competitor and a disruptor for the traditional hospitality industry (Oskam, 2016).

In studying the networked hospitality market leader, this report seeks to shed light on the relationship between pricing and its determinants. Specifically, accommodation rental offers in Rotterdam listed on Airbnb are investigated using a hedonic pricing model. Different variables are explored in order to examine if and how different listing characteristics are reflected in the price.

1.2. Pricing

Pricing is widely acknowledged to be one of the most important factors determining the long-term success of the hospitality industry (Hung et al., 2010; Wang and Nicolau, 2017a). Due to the unique characteristic of perishability, meaning that a room cannot be stored away but rather must be sold each given night, pricing and revenue management have been identified as two of the most frequently researched topics within the accommodation business (Yoo et al., 2011). The price of a hotel room influences consumer's decision-making and profitability of the hotel, and therefore it is crucial to understand pricing (Gibbs et al., 2017).

Recognizing the importance of pricing to the overall hospitality industry, it could be argued that pricing is one of the most important business practices for Airbnb hosts to master. Due to the strong growth of Airbnb, hosts are increasingly facing greater competition and strategic pricing becomes crucial. However, understanding Airbnb prices not only provides insights of practical importance to hosts, but also to researchers, hospitality professionals and municipalities trying to understand the sharing economy accommodation phenomenon (Gibbs et al., 2017).

According to a research study of Hill (2015), hosts are having difficulty with making pricing decisions and determining the real market value of their listing. The uniqueness of their offerings on Airbnb makes it very difficult to set efficient prices. In order to tackle this problem, Airbnb introduced a pricing tool, offering new daily price tips to help hosts set prices optimally. The tool is based on an algorithm that takes into consideration a large number of factors, but lacks transparency (Gibbs et al., 2017). Hence, this study will give insights in the price determinants of Airbnb and will hereby create more transparency.

Although Airbnb has become both a competitor and a disruptor for the traditional hospitality industry, only a few researches have investigated the factors determining the price of sharing economy based accommodation (Gutt and Herrmann, 2015). The number of publications does not yet reflect the importance, which the disruptive business model of networked hospitality has acquired (Teubner et al., 2017; Oskam, 2016). This study contributes to the limited body of literature related to Airbnb and pricing and explains which variables make up the price of a listing, and therefore indicate how Airbnb host set their prices and if they systematically link their prices to the characteristics of their listing. The study analyzes how characteristics of Airbnb listings influence the price of Airbnb in Rotterdam, a secondary tourist destination of growing popularity in the Netherlands.

2. Literature review

2.1. Background of Airbnb

Collaborative consumption

The sharing economy is a socio-economic system that allows for shared creation, production, distribution and consumption of goods and services among individuals (Tussyadiah and Pesonen, 2015). It is a major disruption that is happening across the globe, reversing business models and driving companies and individuals to rethink the use of underutilized assets (PWC, 2015).

The emerge of collaborative consumption, has been enabled by two key factors: technological progression and supply-side flexibility (Bostman and Rogers, 2011; Zervas et al., 2016; Wang and Nicolau, 2017a). Technology innovations have empowered individuals to create their own content, share information and conduct transactions via online platforms and market places (Kaplan and Haenlein, 2009; Zervas et al., 2016; Wang and Nicolau, 2017a). Likewise, supply-side flexibility enables collaborative consumption as suppliers can easily list and de-list the variety of goods and services offered on the peer-to-peer platform (Zervas et al., 2016).

The sharing economy phenomenon is arguably reshaping the market place. Collaborative consumption takes many forms, including the rental of houses, car sharing, asset sales, credit unions and the provision of freelance labor (Lamberton, 2015; Wang and Nicolau, 2017a). As a term, ''sharing'' can be related to notions of gifts and favors. Nonetheless, many peer-to-peer platforms explicitly involve monetary negotiated exchanges (Lampinen and Cheshire, 2016).

Sharing economy based accommodation rental

Sharing economy based accommodation rental has shown rapid growth as a result of high tourist demand (Guttentag, 2015; Heo, 2016), with Airbnb being the leading platform (Wang and Nicolau, 2017b). Airbnb disrupts the traditional hospitality industry: instead of a single company managing buildings, terms and leases, Airbnb facilitates connections between hosts who rent spaces in their homes or secondary properties and guests from around the world (Lampinen and Cheshire, 2016).

Airbnb describes itself as ''a trusted community marketplace for people to list, discover and book unique accommodations around the world (Airbnb, 2017a)''. Joe Gebbia, Airbnb CPO, puts the emphasis on ''commerce with the promise of human connection'' (Gebbia, 2016).

Airbnb listings range from entire homes, to private or shared rooms in an accommodation where the host is also present, and the involve very modest to extremely luxurious accommodations (Guttentag, 2015; Wang and Nicolau, 2017b). The networked hospitality leader enables potential guests to search for accommodation based on destination, travel dates and number of guests. The website then displays a list of available listings that can be redefined by characteristics, including neighborhood, price and amenities. Also, specific listings can be selected for more details such as a description, reviews and photo's. If the potential guest is interested in an accommodation, a message can be sent to the host, with the possibility to ask questions. Subsequently, the host can ask questions in return and may accept or reject the reservation. Payments are made through the Airbnb website (Guttentag, 2015).

Motivations for Participation

Several studies have investigated social and psychological aspects of the sharing economy based accommodation phenomenon, such as the motivation of hosts and guests. From the perspective of hosts, a study of Ikkala and Lampinen (2015) found Airbnb hosts in Finland to be motivated by both financial and social reasons. Building upon this study Lampinen and Cheshire (2016) illustrate that the financial benefits of hosting do not necessarily crowd out intrinsic motivations, including social exchange and interpersonal interaction, for hosting but instead strengthen them.

According to Guinby and Gasdia (2014) travelers stated better value for money and more space as the top reasons to choose for sharing economy based accommodation rental. Similarly, Balck and Cracau (2015) argue that guests point out cost reduction as the main reason to choose for peer-to-peer accommodation instead of hotels. Moreover, Tussyadiah (2014) surveyed peer-to-peer short-term rental users and found that they were motivated by three key factors, being community, sustainability and economic benefits, with economic benefits being the most significant. Additionally, Nowak et al. (2015) conducted a study with US and European Airbnb guests and concluded that the top five reasons to rent an Airbnb are cheaper price, location, authentic experience, own kitchen and uniqueness of the unit.

Similarly, Guttentag (2015) has examined Airbnb guests' motivations for using the platform and proposed three appeals of the service: price, amenities and authenticity. The findings suggest that guests choose peer-to-peer accommodation over traditional hotels as it provides a wide range of prices and property features, as well as a more diversified experience. Renting an Airbnb property, allows people to create social connections, since guests are able to have direct interactions with hosts and to connect with local communities (Tussyadiah and Pesonen, 2015).

2.2. Hedonic Pricing in the Traditional Accommodation Industry

Hedonic pricing

Hedonic pricing theory claims that the price of a product can be derived from measurable attributes or characteristics of the product (Rosen, 1974). According to this theory, the price of an Airbnb listing can be associated with the presence or absence of certain characteristics. In other words, the listing price reflects the hosts' perception of guests' willingness to pay for certain listing characteristics (Gibbs et al., 2017).

Hedonic pricing theory uses multiple regression analysis to investigate the correlation between characteristics and the price of the product (Rosen, 1974). The theory has been regularly used in research regarding the accommodation industry, including hotels, holiday apartments and bed and breakfasts (Gibbs et al., 2017). From the perspective of the traditional accommodation industry, typical price determinants are: quality signaling factors, location, amenities and services, property characteristics and market characteristics (Wang and Nicolau, 2017b; Teubner et al., 2017; Gibbs et al., 2017).

Quality signaling factors

The first category of traditional accommodation price determinants is quality signaling factors. Quality signaling factors offer buyers information on the quality of the accommodation (Yang et al., 2016). Hotel quality signaling factors include chain affiliation, star rating and customer rating (Wang and Nicolau, 2017b). Firstly, hotel rates are higher if hotels are affiliated with branded chains (Thrane, 2007; Chen and Rothschild, 2010; White and Mulligan, 2002; Becerra et al., 2011) Secondly, high star ratings are one of the main positive drivers for price (Schamel, 2012; Zhang et al., 2011; Yang et al., 2016; Becerra et al., 2011; Chen and Rothschild, 2010). Thirdly, using a sample of hotels in the Caribbean islands, Yang et al. (2016) show that high customer ratings have a significant positive influence on the price. Similarly, Schamel (2012) explores the effect of customer ratings, and find that positive customer ratings lead to a higher price.

Location

The second category of traditional accommodation price determinants is location. Several studies on the influence of location on accommodation price show that a shorter distance from a focal point, such as the city center, train station or major attraction, is associated with a higher price (Wang and Nicolau, 2017b; Schamel, 2012; White and Mulligan, 2002; Zhang et al., 2011). For example, Thrane (2007), identified the relationship between location and price of 78 hotels in Oslo and found that hotels located close to the train station in the city center had a higher average daily rate. However, these findings are not replicated by Chen and Rothschild (2010), who based on a study of 73 hotels in Taiwan, detect that hotels in the city center were less expensive than hotels located outside of the city center. With respect to holidays hotels in the sun-and-beach segment, a shorter distance from the beach is correlated with a higher price (Coenders et al., 2013; Saló and Garriga, 2011).

Amenities and services

The third category of traditional accommodation price determinants is amenities and services. Several research studies state that hotels that provide amenities, including hair dryers, mini-bars, televisions and safes consistently charge higher prices (Becerra et al., 2011; Yang et al., 2016; Zhang et al., 2011; Schamel, 2012). Moreover, the provision of services such as room service, a late checkout and advance booking are positively correlated with a higher price (Schamel, 2012; Yang et al., 2016).

Property characteristics

The fourth category of traditional accommodation price determinants is property characteristics. One of the most important property characteristics for hotels is parking. Amongst city-based hotels, parking increased the price from 7.4% to 19% (Coenders et al., 2013; Thrane, 2007; Juaneda et al., 2011). Other meaningful property characteristics of hotels are fitness centers. Chen and Rothschild (2010) determined that hotels with fitness centers charged prices that were 26.7% higher than hotels without fitness centers.

Moreover, Saló and Garriga (2011) analyzed the price of second-home rentals in Spain, and found that the rental price of holiday apartments were 10.9% lower than the price of terraced houses, and detached houses were 13.8% more expensive than terraced houses.

Also, they identified that an additional room increases the rental price by 13,8%. Likewise, Juaneda (2011) concur in their study that an extra room in a holiday apartment generated an additional 20,6% in price. Fleischer (2012) measured the influence of views on the price of hotels situated on the Mediterranean Sea. Hotel room prices were found to be about 10% higher for a room with a view than for one with no view specification.

Market and industry characteristics

The last category of traditional accommodation price determinants is market and industry characteristics. Yang et al. (2016) found that high flight costs, which means low market accessibility, lead to lower hotel prices. Moreover, Becerra et al. (2011) show that the number and proximity of competitors influence the price.

2.3. Airbnb Pricing

Background of hosts

Airbnb hosts are acting as sharing economy entrepreneurs, social media marketers and hospitality providers, selling accommodation to prospective guests. However, hosts generally have little general business or hospitality knowledge, which gives them a unique position in the tourist industry (Gibbs et al., 2017). Ikkala and Lampinen (2014a) performed qualitative interviews with Airbnb hosts, and found that they price their listings below the market price in order to be able to choose guests from a wider pool of candidates.

Using a data set of Airbnb listings in Chicago, Li et al. (2015) evaluate differences in the operational and financial performance of professional hosts (with two or more properties) and non-professional hosts (with only one property). They found that properties managed by professional hosts earn 16.9% more in daily revenue and have 15.5% higher occupancy rates, compared with properties owned by nonprofessional hosts. Also, their data suggests that professional hosts are less likely to leave the market place. These differences can be explained by pricing inefficiencies of nonprofessional hosts, meaning that professional hosts involve in more intense pricing activities and respond better to moments of higher demand.

Furthermore, several studies have explored differences in pricing caused by racial backgrounds of hosts. Edelman and Luca (2014) tested racial discrimination against hosts of Airbnb in New York, using a data set that combines hosts' pictures with the listed price. They concur that non-black hosts charge approximately 12% more than black hosts on comparable properties. Moreover, a related study on racial discrimination by Kakar et al. (2017), examined the effect of racial backgrounds of host on the price of Airbnb listings in San Franciso. They find that Asian and Hispanic hosts charge 8% to 10% lower prices compared to their white counterparts. They suggest that minorities charge lower prices because they either expect discrimination on the peer-to-peer platform or prefer to increase demand in order to achieve occupancy targets or attract more potential guests.

Unique characteristics

Airbnb has many unique listing characteristics, such as instant booking and the cancellation policy that could be important price determinants (Gibbs et al., 2017). Furthermore, trust is considered to be of high importance for the sharing economy accommodation rental (Teubner et al., 2017;

Bostman and Rogers, 2011; Hawlitschek et al., 2016; Ert et al., 2016) Airbnb hosts' income clearly depends on how much demand they are able to attract at a certain price. Also, the entire process of selecting a listing and sending a booking request is conducted online, which makes the information showed on the Airbnb website the only reference point for potential guests (Hawlitschek et al., 2016).

Hence, trust is crucial to change a potential guests' interest into a booking request (Teubner et al., 2017; Hawlitschek et al., 2016; Gebbia, 2016) For this reason Airbnb has implement different tools to facilitate trust between hosts and guests, including review systems, personal pictures and profiles and mutual rating (Gebbia, 2016; Teubner et al., 2017; Kakar et al., 2017). The effects of trust tools on the price of Airbnb listings have been analyzed in several studies. Wang and Nicolau (2017b) find that hosts with a Superhost status, more listings and verified identities usually charge higher prices.

Similarly, research of Liang et al. (2017) shows that guests are willing to spend more on superhosts accommodations and Gibbs et al. (2017) demonstrate that a Superhost badge and higher star ratings consistently translate into price premiums. Using a data set of more than 5000 Airbnb listings in Austin, Texas, Xie and Mao (2017) estimate the effects of host attributes on listing performance. The study reveals that characteristics such as Superhost badge, response rate and operating experience are positively correlated with the number of reservations.

Gutt and Herrmann (2015) empirically investigate how Airbnb hosts in New York adjust their prices once their listings get a visible star rating for the first time. The findings indicate that hosts whose listings achieve star rating visibility significantly increase their prices by an average of €2.69 more than hosts with equivalent listings who do not experience this rating visibility. Interestingly, these studies also show that more reviews are associated with a drop in price (Gutt and Herrmann, 2015; Wang and Nicolau, 2017b; Xie and Mao, 2017; Liang et al., 2017). A possible explanation could be that lower prices attract more bookings (Wang and Nicolau, 2017b). Based on a data set of Airbnb listings in Germany, Teubner et al. (2017) find that hosting rating scores, accommodation photographs and duration of membership significantly impact price.

3. Research methods

3.1. Data collection

The population of this research project consists of all Airbnb properties in Rotterdam since its launch in 2008. For this research report primary data has been used to perform quantitative research on a large-scale data set of Airbnb listings in Rotterdam obtained by AirDNA (AirDNA, 2017). AirDNA is an analytics platform that provides data packages of Airbnb by scraping data from information publicly available on the Airbnb website. Web scraping is the defined process of extracting and combining contents of from the web in a systematic web (Glez-Peña et al., 2013). The dataset contained 6.591 Airbnb listings located in The Hague and Rotterdam in the period August 2010 – February 2017.

The sample used for this research study is the scraped data provided by AirDNA. The first scraped data available are from 6 August 2010 and the last scraped data are from 10 February 2017. For this reason, the sample size is all Airbnb properties in Rotterdam that are active on the platform since 6 August 2010 till 10 February 2017, and from which all necessary data could be scraped. Airbnb properties listed after 10 February are not included in the analysis. In total, 1370 listings are included in the multiple linear regression analysis. Unfortunately, the data set provided for this research report limits the number of listing characteristics that could be investigated. For this reason, 14 variables are examined, divided in the following four categories: host characteristics, site and property characteristics, rental rules, and reputational characteristics. While this research included traditional accommodation price determinants including location, customer reviews and capacity, the analysis also took into account host characteristics and rental rules, as suggested by the literature on this topic, such as the superhost badge and the cancellation policy. Response rate was excluded from the model due to its great amount of missing values

3.2. Measuring instruments

In order to examine if and how different listing characteristics are reflected in the price, average daily rate (ADR) was taken as dependent variable. The effects of 14 listing characteristics (independent variables) are tested and divided in the following four categories: host characteristics, site and property characteristics, rental rules, and reputational characteristics.

Variable	Description
Dependent	
Price	Average daily rate (ADR) measured in Euro
Independent	
Host characteristics	
Superhost Badge	Being a Superhost: they have hosted at least 10 trips; maintained 90% response rate or higher; received a 5-star review at least 80% of the time they have been reviewed as long as at least half of the guests who stayed left a review; completed each of their confirmed reservations without cancelling (Airbnb, 2017c)
Number of listings	Host's number of accommodation rentals listed on Airbnb
Site and Property Characteristics	
Distance to the city center	The distance (KM) between the location of a listing and the municipally of Rotterdam
Number of bedrooms	The number of bedrooms
Listing type	Either an entire home, private room or shared room
Business Ready Status	The listing is an entire home and includes 24-hour check-in; Wi-Fi; a laptop-ready workspace; smoke and carbon monoxide detector and amenities such as hairdryers, hangers, an iron and shampoo (Airbnb, 2017h)
Created date	Date on which the rental was first listed
Max number of guests	Maximum number of guests
Rental rules	
Cancellation policy	Either flexible, moderate or strict (Airbnb, 2017b)
InstantBook	The guest can place a reservation without explicit approval from the host (Airbnb, 2017g)
Reputational Characteristics	
Number of bookings	The ratio of total number of bookings over the years that the rental was first listed
Number of reviews	The ratio of total number of review over the years that the rental was first listed
Overall rating	Overall review scores, 1- 5 (Airbnb, 2017d)
Number of photos	The number of pictures of the listing

Table 1 independent and dependent variables used in multiple linear regression analysis

3.3. Statistical testing

As outlined in the literature review, hedonic price modeling assumes that the listing characteristics will be reflected in the price and that by regression analysis the individual impact of the various characteristics can be quantified. Hence, multiple linear regression analysis is used to detect relationships between the dependent variable and a set of independent variables (Rosen, 1974; Gibbs et al., 2017; Wang and Nicolau, 2017b; Teubner et al., 2017). Multiple linear regression analysis is an extension of simple linear regression analysis, because it assesses the association between two or more independent variables and a single dependent variable. In other words, it decomposes the unique contribution of each variable as predictor of ADR, and takes into account the correlations between the different independent variables. In the least-squares model, the best-fitting line for the observed data is calculated by minimizing the sum of the squares of the vertical deviations from each data point to the line. The multiple linear regression analysis is used to identify the strength of the effect that the independent variables have on the dependent variable and to understand how much the dependent variable will change when the independent variable changes (Stats, 2011; Statistics Solutions, 2017).

3.4. Data analysis procedures

Preparation of the dataset

Select Rotterdam properties
The data set provided by AirDNA contained of a total of 6,591 Airbnb listings of which 3,021 in The Hague and 2,570 in Rotterdam. Since this research study is focused on Airbnb listings in Rotterdam, all the Airbnb listings in The Hague were taken out of the data set. Additionally, the listings were checked on their actual location and listings that were not located in areas that are part of the municipality of Rotterdam were taken out of the data set as well. This reduced the amount of properties to 2,567.

FIGURE 1 Municipality Rotterdam (Gemeente Rotterdam, 2017).

Outlier ADR
Also, the data set contained of some listings without scraped ADR. This reduced the data set to 1,921 properties. Listings with an ADR of 274.59, i.e. a z-value larger than 3.29 were eliminated as outliers. This reduced the amount of properties to 1,891.

Recode into new variable
The variable created date has been converted to a new variable: ListedMonths, meaning the difference between the date of my analysis (8 December 2017) and the created date expressed in the number of months, in order to perform a better analysis.

Dummy variables
In order to include nominal and ordinal variables in the multiple regression analysis, the variables' categories are converted into dummy variables with 0/1 coding. The variable number of listings has been recoded into two dummy different variables: professional hosts (2+ listings) and nonprofessional hosts (1 listing), since more valuable conclusions could be written.

Superhost	Yes = 1; No = 0
Nonprofessional	Reference
Professional	Yes = 1; No = 0
Entire home	Reference
Private room	Yes = 1; No = 0
Shared room	Yes = 1; No = 0
Business ready status	Yes = 1; No = 0
Flexible	Reference
Moderate	Yes = 1; No = 0
Strict	Yes = 1; No = 0
Instant booking enabled	Yes = 1; No = 0

TABLE 2 Code Book Dummy Variables

Test assumptions
Multiple linear regression analysis makes several key assumptions, which were checked (Statistics Solutions, 2017).

1. Multivariate Normality

Multiple regressions assume that the errors between observed and predicted values (i.e., the residuals of the regression) are normally distributed. This assumption has been checked by looking at a histogram and a normal p-p plot (Statistics Solutions, 2017) (figure 2 and 3).

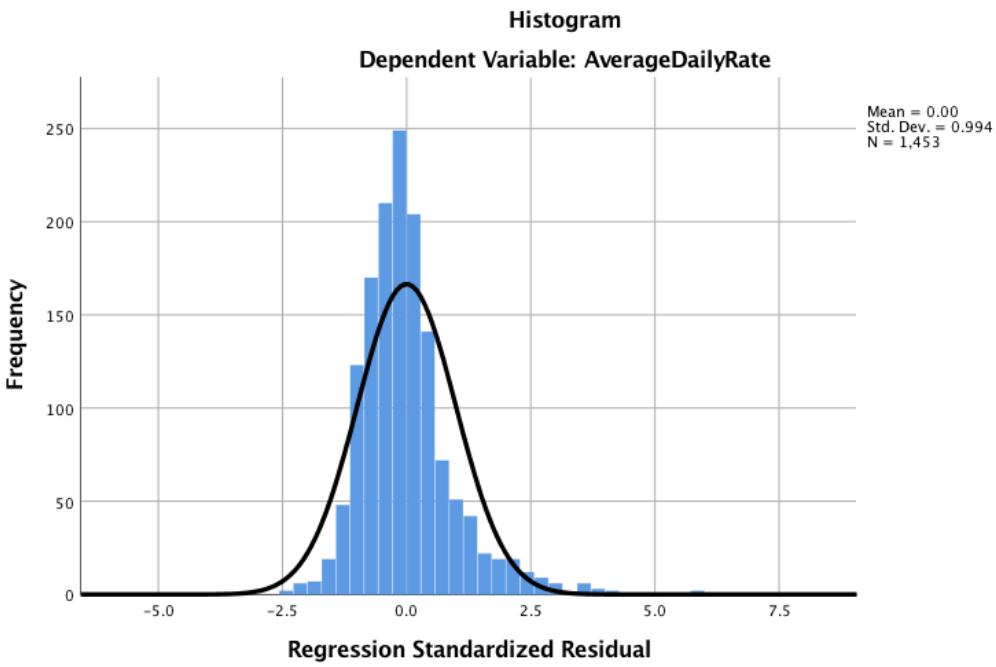


FIGURE 2 Histogram Regression Standardized Residual (ADR)

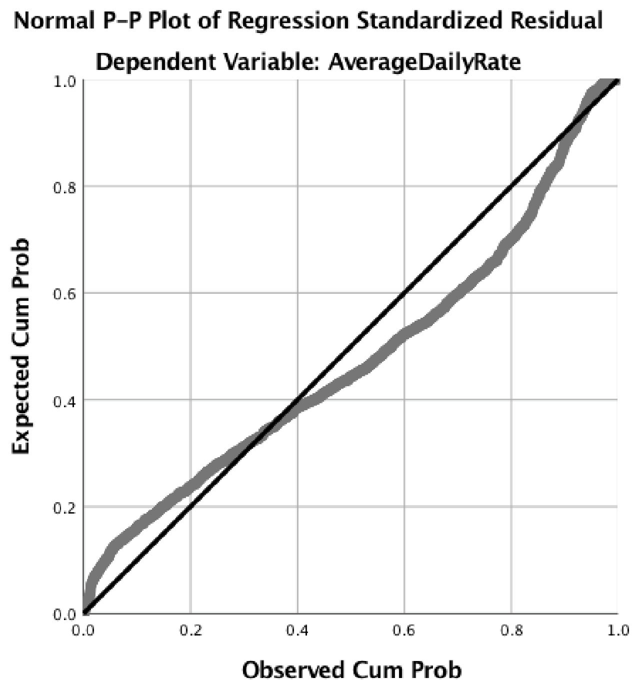


FIGURE 3 Normal P-P Plot of Regression Standardized Residual (ADR)

The histogram shows a quite unregular distribution of the residuals associated with listing characteristic. Also, the values in the plot are not very close to the line of least squares, the line of the greatest fit. This might indicate multivariate abnormality.

2. No multicollinearity

Multiple regressions assume there is no multicollinearity in the data, which occurs when the independent variables are too highly correlated with each other (Statistics Solutions, 2017) . Multicollinearity is checked by assessing the Pearson's correlations among all independent variables. The highest correlations are found between the number of bookings and the number of reviews (r = 0.729) and between the number of bedrooms and the max number of guests (r= 0.699) (appendix 6.2, table 7). However, all the correlations between the independent variables are less than 0.80. Moreover, the Variance Inflation Factors (VIF) of the multiple linear regression have been checked and are all smaller than 10. Hence, no multicollinearity issues exists (Gibbs et al., 2017; Statistics Solutions, 2017).

3. Homoscedasticity

The last assumption of multiple linear regressions is homoscedasticity, which states that the variance of error terms are similar across the values of the independent variables (Statistics Solutions, 2017). A plot of standardized residuals (ZRESID) versus predicted values (ZPRED) has been created to indicate whether points are equally distributed across all values of the independent variables (figure 4). Heteroscedasticity is present when the variance associated with the residuals of the dependent variable are not homogenous across levels of the independent variable. The strength of the prediction of the regression equation should be equally strong across all levels of the independent variables (Stats, 2011). The cone-shaped pattern in figure … shows that the data might be heteroscedastic.

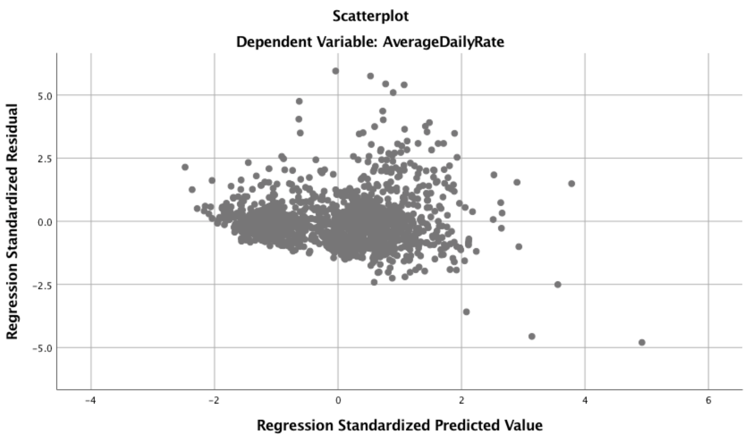


FIGURE 4 Plot of Standardized Residuals Vs Standardized Predicted Values (ADR)

Logarithmically transform data

When the residuals of the regression are not normally distributed and the data is heteroscedastic, a non-linear data transformation offers a solution (Statistics Solutions, 2017). For this reason, the Y (ADR) has been logistically transformed. Whereas in the equation Y = a + bX, a unit increase in X is associated with an average of b units increase in Y, in the equation Ln(Y) = a + bX, a unit increase in X is associated with an average of b% increase in Y (Statistics Solutions, 2017). The log transformation has resulted in the following histogram and plots (figure 5 and figure 6).

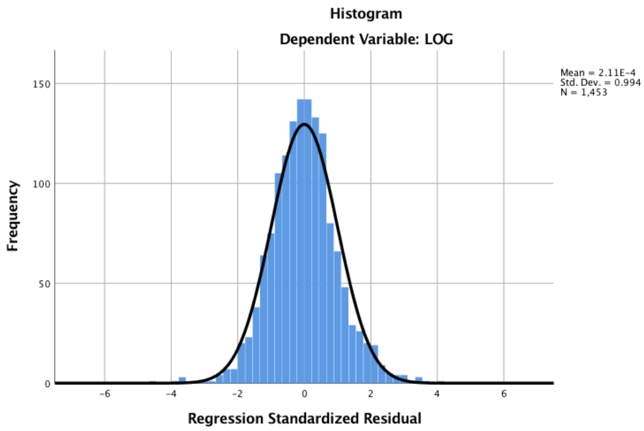


FIGURE 5 Histogram Regression Standardized Residual (LOG ADR)

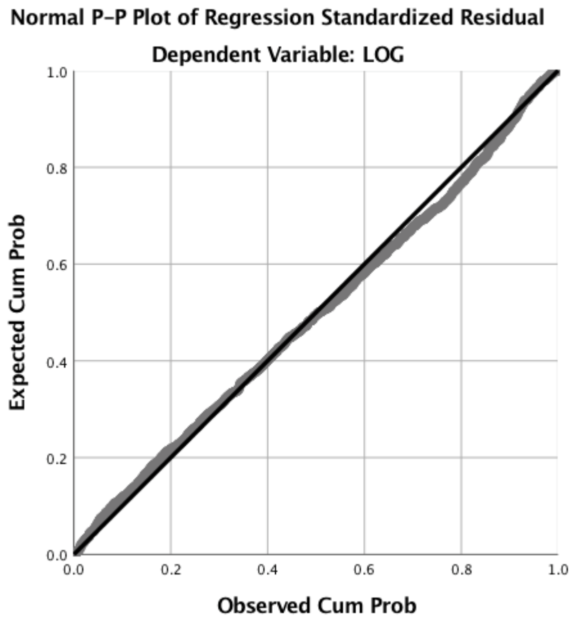


FIGURE 6 Normal P-P Plot of Regression Standardized Residual (Log ADR)

The histogram in figure 8 indicates that after the log transformation the residuals associated with listing characteristics are equally distributed. Moreover, the plot in figure 9 shows that the values are now ‘‘hugging’’ the line of least squares.

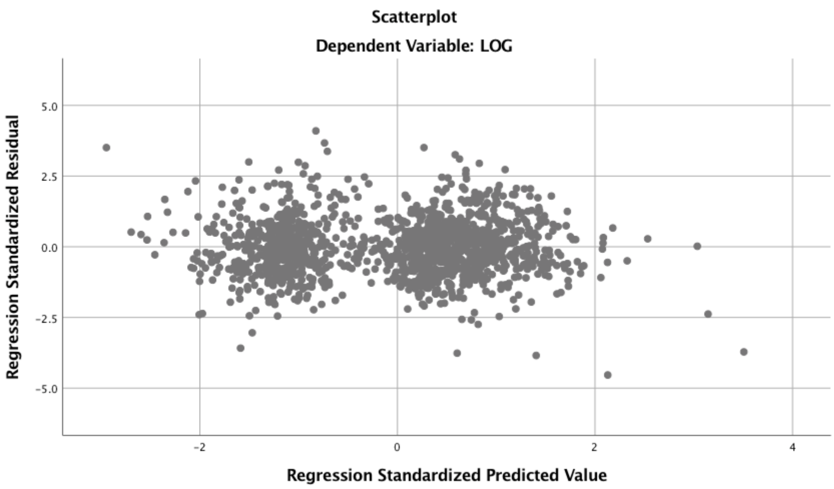


FIGURE 7 Plot of Standardized Residuals vs Standardized Predicted Values (Log ADR)

The cone-shaped pattern has disappeared after the log transformation, which indicates that the data is probably homoscedastic (figure 7). To be 100% certain about this assumption, a Breusch-Pagan test should be performed (Gibbs et al., 2017). However, due to administrator limitations in SPSS the test could not be executed. It should be noted that even when the data might still be heteroscedastic, it would not violate the results presented due to the large sample size (Gibbs et al., 2017).

Descriptive statistics

Descriptive statistical tests have been performed, to give a better overview of the dependent and independent variables. The data set contained of 1,891 listings, and for the descriptive statistics all listings with available data are taken into account.

Statistical analysis

After the data set was prepared, the multiple regression analysis could be conducted. The multiple regression analysis included 1,370 Airbnb listings, as it can only take into consideration Airbnb listings with zero missing values.

The following multiple regression model has been formulated:

$$Ln(ADR)_i = \beta0 + \beta1SuperhostBadge + \beta2Professional + \beta3DistanceTo + \beta4NumberOfBedrooms + \beta5Private + \beta6Shared + \beta7BusinessReady + \beta8ListedMonths + \beta9MaxGuests + \beta10Moderate + \beta11Strict + \beta12InstantBook + \beta13NumberOfBookings + \beta14NumberOfReviews + \beta15OverallRating + \beta16NumberOfPhotos + U_i$$

The coefficients represent the percentage change in price when the independent variables change by 1. The price effect of the dummy coded variables on the log dependent variable is quantified by $e^b - 1$, with b being the coefficient and e standing for the base of the natural logarithm (Gibbs et al., 2017; Wang and Nicolau, 2017b)

The stepwise multiple regression method has been applied in SPSS. Stepwise only includes statistically significant contributors to the multiple linear equation. It looks into the correlation matrix and chooses the independent variable that has the largest Pearson correlation with the dependent variable. It puts it into a regression and calls it model one, then it goes back to the correlation matrix and looks to the next highest predictor of the dependent variable, controlling for variance in the first predictor. It does that sequentially; it keeps going back to the semi-partial correlations and looks for the next biggest predictor of the dependent variable. And once it finds a non-significant predictor it stops the analysis (Stats, 2011). After the results of the multiple regressions have been analyzed, a conclusion and recommendations were written.

Limitations

Demand side
The research study used the ADR as dependent variable and this does not take into account the demand side by for example weighting the ADR by the occupancy rate. For this reason, no conclusions can be made about the accuracy of the host's perception and economic success of their pricing strategy.

One price point / average price
Moreover, only one average price is used in the research study. Hence, the influence on price of different seasons, special events and moment of the week (weekdays vs. weekends) are not taken into account.

Limited independent variables
The research does only consider a limited amount of variables. As suggested in the literature review other factors could also be taken into account, such as the presence or absence of amenities and special services offered (late check-in, breakfast). Also, the research model does not include market competition and other external factors. The large variety in the types of properties makes it very difficult to model competition, and therefore it was not possible to take into account. Hence, the research study cannot make conclusions about if and how hosts include competition in their pricing decisions.

Data reliability
The data was scraped and provided by AirDNA. Since the data was scraped from information publicity available on the Airbnb site, there might be inaccuracies in the data, which could potentially harm the results. The reserved status is extrapolated by AirDNA from historical data.

Lack of segmentation
Different target markets (for example business travelers vs. leisure travelers) are not involved in this research study, and therefore the research assumes that hosts focus on one equal consumer market. Hence, no statements can be made about price differences between different target groups.

Lack of price areas
Also, no interquartile ranges of the ADR are applied for indicating a significant difference among certain price ranges. For example, the distance to the city center could have a greater price effect for high-priced properties than for low-priced properties. Since the research does not include quantiles, no conclusions can be made about different effects of the listing variables for the various price ranges.

Lack of multiple focal points
The research takes into consideration only one focal point (the municipally) to indicate the effect of location on the listing price. However, Rotterdam might have multiple focal points, such as the harbor and some other specific tourist areas that could have a price effect on the listings.

Lack of psychological and social factors
The research study aims to create a better understanding of host behavior and perception about price. However, no psychological and social factors are taken into account that indicates the rational for hosts' price decisions.

4. Results

In the following paragraphs, the results are presented and the research questions are answered. The SPSS output of the descriptive statistical tests and the multiple linear regression analysis can be found in appendix 6.1 and appendix 6.2.

4.1. Data analysis

In order to give a better understanding of the data set, a frequency table and histogram of ADR has been created to display the distribution of Airbnb listings in Rotterdam by ADR (table 3 and figure 8). The ADR ranges from €10.00 to €261.67. On average the ADR is €78.62. Most listing prices range between €50.00 – €99.99 (44.8%).

Price range	Frequency	Percentage	Cumulative percentage
€0.00 – €49.99	554	29.3%	29.3%
€50.00 – €99.99	847	44.8%	74.1%
€100.00 – €149.99	366	19.4%	93.4%
€150.00 – €199.99	93	4,9%	98.4%
€200.00 – €249.99	23	1.2%	99.6%
€250.00+	8	0.4%	100%
Total	1,891	100%	

TABLE 33 Distribution of Airbnb Listings In Rotterdam By Average Daily Rate

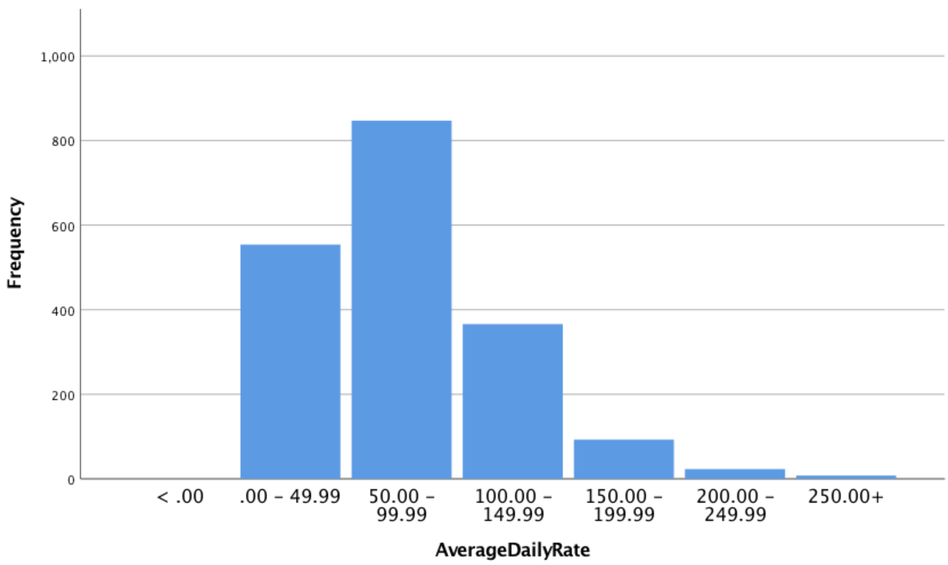


FIGURE 8 Histogram Average Daily Rate

In order to identify the determinants of the price of Airbnb listings in Rotterdam, the influence of the listing characteristics on the ADR in logarithmic form is assed. Appendix 6.2 displays the output of the multiple regression analysis conducted in SPSS. In the 11th model of the stepwise multiple regression analysis 11 dependent variables are included, which are: private rooms, shared rooms, max number of guests, number of photos, distance to the city center, overall rating, number of bedrooms, listed months, number of reviews, moderate cancellation policy, strict cancellation policy. Table 4 and table 5 demonstrate the main results of the multiple regression analysis. Table 4 includes the independent variables that have a statistically significant influence on price. Table 5 presents the independent variables that do not have a statistically significant influence on price. The beta coefficients represent the percentage change in price when the independent variables change by 1. The price effect of the dummy coded variables on the log dependent variable is quantified by $e^b - 1$, with b being the coefficient and e standing for the base of the natural logarithm (Gibbs et al., 2017; Wang and Nicolau, 2017b). For this reason, ad additional column % change is added to the table.

Variables	P-value	Correlation Coefficient	Beta Coefficient	% Change	Standard Error
Private*	0.000	-0.547	-0.522	-40.68%	0.022
Shared*	0.000	-0.373	-0.947	-61.20%	0.064
MaxGuests	0.000	0.162	0.047	4.75%	0.008
NumberofPhotos	0.000	0.221	0.008	0.75%	0.001
DistanceTo	0.000	-0.207	-0.051	-5.11%	0.007
OverallRating	0.000	0.131	0.095	9.52%	0.020
NumberofBedrooms	0.000	0.118	0.074	7.42%	0.017
ListedMonths	0.000	0.111	0.003	0.29%	0.001
NumberOfReviews	0.000	-0.108	-0.001	-0.14%	0.000
Moderate*	0.001	0.089	0.071	7.36%	0.021
Strict*	0.002	0.082	0.072	7.50%	0.024
Constant	0.000	3.645			0.097
Model information					
F-value	176.159				
Adjusted R^2	0.585				
P-value model	0.000				
Durbin Watson	1.188				

* Binary variables

TABLE 44 Significant Predictors of Ln(ADR); Multiple Regression Analysis SPSS

Variable	P-value	Correlation Coefficient
Superhost*	0.210	0.034
Professional*	0.258	-0.031
BusinessReady*	0.434	-0.021
InstantbookEnabled*	0.564	0.016
NumberOfBookingsLTM	0.479	-0.019

TABLE 55 Unsignificant Predictors of Ln(ADR); Multiple Regression Analysis SPSS

The ANOVA table (appendix 6.2, table 10) is testing sequentially the statistical significance of the model as it adds more and more independent variables. The F value in the 11th model 176.159 and the model is statistically significant (p-value = 0.000; p-value < 0.05). The adjusted R^2 of 0.585 indicates that 58.5% of the variance in ADR can be accounted for by the independent variables. The Durban Watson of 1,188 (smaller than 1.5) shows that the data has meaningful serial correlations (Stats, 2011).

Results

1. Host characteristics

1.1 What is the price effect of the Superhost Badge on Airbnb listings in Rotterdam?

The superhost badge represents hosts who provide a perfect example for other hosts, and extraordinary experiences for their guests. Hosts can receive the superhost badge when they fulfill specific criteria: they have hosted at least 10 trips in their listing in a year; received a 5-star review at least 80% of the time they have been review as long as at least half of the guests who stayed left a review; maintained a 90% response rate or higher by responding to guests quickly and honored confirmed reservations without cancelling (Airbnb, 2017c).

The superhost badge could provide valuable information to guests: for example knowing that a host never cancels confirmed bookings, could reduce the risk of a trip. A superhost badge is associated with outstanding quality and is expected to help the host to build reputation and enhance trust (Teubner et al., 2017). According to Liang et al. (2017) it draws significant attention to potential guests since it is provided by Airbnb, an independent party, and clearly visible on the online platform. Not to mention that guests can even specifically select superhost listings when they are in search for available rental (Teubner et al., 2017).

The descriptive statistics reveal that in Rotterdam only 7.28% of hosts have a superhost badge and 92.72% of hosts do not have a superhost badge. A possible explanation for this imbalance could be that the superhost badge represents a unique combination of listing characteristics (Teubner et al., 2017).

Surprisingly, the multiple regression analysis indicates that hosts do not use this unique feature for price premiums. There is no significant difference in ADR between hosts who do have a superhost badge and hosts who do not have a superhost badge (p-value = 0.211, p-value > 0.05).

As the superhost badge fails to influence price, the superhost badge might not be as important as some may expect (Gibbs et al., 2017).

1.2 What is the price effect of the number of listings on Airbnb in Rotterdam?

The variable number of listings is equal to host's number of accommodation rentals listed on Airbnb, in Rotterdam and in other cities as well.

The number of listings ranges from 1 listing to 37 listings. The variable has been recoded into two dummy variables: professional hosts (with 2 or more listings) and non-professional hosts (with only 1 listing). In Rotterdam, 61.2% of units are offered by non-professionals and 38.8% are offered by professionals.

It can be concluded that there is no significant difference in ADR between listings operated by professional hosts and non-professional hosts (p-value = 0.260; p-value > 0.05). This result does not correspond with findings of other research studies in which professional hosts charge higher prices than non-professional hosts because professional hosts with multiple Airbnb properties involve in more intense pricing activities, and hereby respond better to moments of high demand and execute more efficient and successful pricing strategies (Li et al., 2015).

. 2. Site and property characteristics

2.1 What is the price effect of the Distance to the city center on Airbnb in Rotterdam?
The distance to the city center, represents the location of the property, and is the difference between the location of the property and the Town Hall of Rotterdam expressed in KM.

Between the Airbnb listings in Rotterdam the distance to the city center ranges from 0.06 KM till 10.8 KM. On average, the distance to the city center is 1.96 KM.

It can be concluded that there is a significant relationship between the location of Airbnb listings and the ADR (p-value = 0.000; p-value < 0.05) The correlation coefficient of -0.207 indicates that there is a weak, negative relationship between the distance to the city center and the ADR. Hence, a longer distance to the city center can be associated with a lower ADR. The linear regression analysis shows that every KM further from the city center leads to a price decrease of 5.11%.

The results are in line with the findings of previous studies of traditional accommodation price determinants (Schamel, 2012; White and Mulligan, 2002; Zhang et al., 2011), and indicate that a shorter distance from a focal point, in this case the municipally of Rotterdam, is associated with higher prices. It can be concluded that hosts expect guests to highly value listings close to the city center.

2.2 What is the price effect of the number of bedrooms on Airbnb in Rotterdam?
The number of bedrooms ranges from 0 to 10. The mode (1) reveals that most listings boast one bedroom (68.3%). Also many listings boast two bedrooms (21.4%).

It can be concluded that the number of bedrooms significantly impacts price (p-value = 0.000; p-value < 0.05). There is a weak, positive relationship between the two variables (r = 0.118). Hence, when the number of bedrooms increases, the ADR increases as well. Each additional bedroom was associated with price increases of 7.4%.

These findings correspond with previous research studies on price determinants of the accommodation industry. Apartments with more bedrooms can accommodate more guests, which significantly increases price (Saló and Garriga, 2011; Juaneda et al., 2011)

2.3 What is the price effect of the listing type on Airbnb in Rotterdam?
The listing type can either be a shared room, a private room or an entire home / apartment. When renting a shared room guests share the entire space with the hosts or other guests. When renting a private room guests share some common areas with the host or fellow guests, such as the kitchen, living room or bathroom, however, they are provided with a private bedroom. With an entire home or apartment guest rent the entire unit and do not have to share the space with the hosts or any other guest (Airbnb, 2017f).

The descriptive statistics illustrate that most Airbnb listings in Rotterdam are an entire home (n = 1196, 63.25%), followed by private rooms (n = 652, 34.48%) and only 43 listings (2.27%) of Airbnb listings are a shared room.

The entire homes have been used as reference category. Hence, the change % of the dummy variables stands for the deviation from this reference category. The multiple regression analysis revealed that there is a significant difference in ADR between entire homes and shared rooms (p =

0.000, $p < 0.05$) and a significant difference between entire homes and private rooms ($p = 0.000$, $p < 0.05$). Private rooms were priced 40.68% lower than entire homes, and shared rooms were priced 61.20% lower than entire rooms.

The main difference between entire homes and private rooms, and entire homes and shared rooms, is that the guests do not have to share any space with another individual. For this reason, an entire home creates a sense of privacy. Hence, the test results show that hosts charge a huge premium for privacy (Gibbs et al., 2017).

2.4 What is the price effect of the business ready status on Airbnb in Rotterdam?
The business ready status is implemented to attract business travellers and help them to know what they can expect when they arrive. In order to achieve a business ready status, the listings need to fulfill specific criteria. The listing must be an entire home and not allow pets living in the property when guests are present. Moreover, the listing must have at least 3 stars rated reviews, of which at least 60% of both the listing's primary reviews, and reviews for cleanliness and accuracy must be 5 star reviews. Also, hosts must have responded to 90% of booking requests within 24 hours over the last year and provide a 7-day cancellation commitment to reservations. Lastly, the listing must also have the certain business travel ready amenities, including Wi-Fi, a laptop-friendly workspace; self check-in; a smoke detector; a carbon oxide detector; essentials; an iron; hangers; a hair dryer and shampoo (Airbnb, 2017h).

The descriptive statistics reveal that most listings are not business ready ($n = 1650$, 87.26%) and only few listings ($n= 241$, 12.74%) are business ready.

The multiple linear regression analysis shows that there is no significant difference in the ADR between listings with a business ready status and listings without a business ready status (p-value = 0.435; p-value > 0.05) This could be explained by the fact that Airbnb very recently introduced this new listing characteristics. Hence, hosts might believe that guests do not see additional value in this feature.

2.5 What is the price effect of the listedMonths on Airbnb in Rotterdam?
The listedMonths variable represents the number of months between the date on which the rental was first listed and the current date of the statistical test (8-12-2017).

The days of existence of the Airbnb range from 11 months till 95 months. On average the listings exists 27 months (26.69).

It can be concluded that there is a weak, positive relation between the number of months existence of the Airbnb listing and the ADR (p-value = 0.000; p-value < 0.05; $r = 0.111$) This means that when the Airbnb listing is longer online on the platform, the ADR is higher. Each additional listed month was associated with a price increase of 0.29%.

This relation could be explained by the fact that if a listing is longer on the platform, the host has a longer duration of membership as well. The longer duration of membership might create trust, as it requires long-term engagement of the host, hence is time-costly and chances are smaller that it is a case of fraud. In addition, when the listing is longer on the platform, the host's experience increases and he/she responds better to moments of high demand, hence may implementing a more effective and successful pricing strategy (Teubner et al., 2017).

2.6 What is the price effect of the max number of guests on Airbnb in Rotterdam?
The maximum number of guests ranges between 1 and 16 guests. The mode (2) reveals that most Airbnb hosts allow two guests in their listing (50.2%). On average, Airbnb hosts allow three (2.87) guests in their listing.

An increase in the maximum number of guests was significantly associated with price increases (p-value = 0.000; p-value > 0.05) The correlation coefficient of 0.221 indicates that there is a moderate, positive relationship between the two variables. Every additional guest allowed leads to a price increase of 4.75%.

Clearly, this listing characteristic corresponds with the number of bedrooms. These results are in line with previous research studies on price determinants of the accommodation industry. Apartments that can facilitate more guests, consistently translate into price premiums (Saló and Garriga, 2011; Juaneda et al., 2011).

3. Rental rules

3.1 What is the price effect of the cancellation policy on Airbnb in Rotterdam?
Airbnb allows hosts to choose among three cancellation policies, flexible, moderate, and strict, which aims to protect both guest and hosts. The main difference between the cancellation policies is the refund amount (flexible = full refund; moderate = full refund; strict is 50% refund) and the time that the guest is able to cancel (flexible = 1 day prior to check-in; moderate = 5 days prior to check in; strict = 7 days prior to check in) (Airbnb, 2017b).

Of all the Airbnb listings, 875 listings offer a flexible cancellation policy (46.3%), 578 listings offer a moderate cancellation policy (30.6%) and 438 offer a strict cancellation policy (23.2%).

The flexible cancellation policy is used as a reference category. It can be concluded that there is a significant difference in ADR between listings with a flexible cancellation policy and moderate cancellation policy (p-value = 0.001; p-value < 0.05) and listings with a flexible cancellation policy and listings with a strict cancellation policy (p-value = 0.002; p-value < 0.05). Airbnb listings with a moderate cancellation policy were priced 7.36% higher than listings with a flexible cancellation policy and Airbnb listings with a strict cancellation policy were priced 7.50% higher than listings with a flexible cancellation policy. Hence, a flexible cancellation policies and lower prices are related.

This relation suggests that hosts with a stricter cancellation policies are driven by rational aspects rather than emotional, they set higher prices and want to secure their income by avoiding last-minute cancellations (Wang and Nicolau, 2017b).

3.2 What is the price effect of the Instant Book enabled option on Airbnb in Rotterdam?
When instant booking is enabled, the guest can place a reservation without explicit approval from the host (Airbnb, 2017g). As Instant Book listings do not require approval from the host before they can be booked, which helps guests plan their trip in an easier way (Wang and Nicolau, 2017b).

Of the 1891 listings, 1606 listings do not have instant booking enabled (84.93%) and 285 listings do have instant booking enabled (15.07%). Hence, most listings do not have Instant booking enabled (mode).

It can be concluded, that there is no significant difference in the ADR between listings that have instant booking enabled and listings that do not have instant booking enabled (p-value = 0.564; p-value > 0.05). For this reason, the instant book option does not lead to price premiums.

4. Reputational characteristics

4.1 What is the price effect of the number of bookings on Airbnb in Rotterdam?
The number of bookings of a listing is the ratio of total number of bookings over the years that the rental was first listed.

The number of bookings of the last twelve months range from 0 bookings till 195 bookings. On average the listings have been booked 16.45 times. However, most listings have only been booked once in the last twelve months (14.3%).

It was expected that number of bookings could be associated with lower prices as low prices stimulate more demand (Gibbs et al., 2017; Wang and Nicolau, 2017b). Surprisingly, it can be concluded that there is no significant relation between the number of bookings and the ADR (p-value = 0.479; p-value > 0.05)

4.2 What is the price effect of the number of reviews on Airbnb in Rotterdam?
The number of reviews is equal to the ratio of total number of reviews over the years that the rental was first listed.

The number of reviews ranges from 0 reviews till 299 reviews. On average the 1,981 listings have 12.94 reviews. However, most listings have zero reviews (21%).

Since hosts that charge lower prices, tend to receive more bookings and consequently the number of reviews increases (Gibbs et al., 2017; Wang and Nicolau, 2017b), it could be concluded that there is a significant weak relation between the number of reviews and the ADR (p-value = 0.000; r= 0.108). Every additional review is associated with a price decrease of 0.14%. These hosts are aware of the unique characteristic of perishability and aim for a high occupancy and try to attract more bookings by charging lower prices, and thus receive more reviews (Wang and Nicolau, 2017b; Gibbs et al., 2017).

4.3 What is the price effect of the overall rating on Airbnb in Rotterdam?
In addition to written reviews, guests can submit star ratings on different categories, including overall experience, cleanliness, accuracy, value, communication, arrival and location. The overall rating score is an aggregate of the different categories scores guests have given for that listing, and ranges from 1 star till 5 stars (Airbnb, 2017d).

Remarkably, the Airbnb listings in Rotterdam have an average star rating of 4.56. In addition, most listings have a 5 star rating (22.2%), and only 5,3% of overall rating scores falls below 4 out of 5 stars. Also the percentiles (25^{th} = 4.4; 50=4,7 and 75^{th}=4.9) and the SD of 0.48 indicate a low variation. There are three possible explanations for this disproportion. Firstly, guests have a natural tendency to avoid conflict and want to keep harmony, and therefore prefer to provide a high star rating. Secondly, personal contact with the hosts leads to social restraints to give low star ratings. Thirdly, the fact that hosts are able to see the previous reviews of potential guests might hold guests from giving low ratings since they are afraid that hosts do not want to rent their property to them when there is a chance that they receive low ratings as well (Teubner et al., 2017).

The multiple regression analysis finds higher star ratings to be correlated with higher rates (p-value = 0.000; p-value < 0.05). The correlation coefficient of 0.118 indicates that there is a weak, positive relationship between the two variables. Moreover, every additional star is associated with a price increase of 9.5%. Hence, hosts tend to increase prices when they receive higher star ratings, which suggest that hosts expect guests to be willing to pay more for listings with a higher star rating.

4.4 What is the price effect of the number of photos on Airbnb in Rotterdam?
The number of photo's ranges from 1 photo till 150 photos. On average the listings have 14.4 photos. Moreover, most listings have 8 photos.

It can be concluded that there is a significant relationship between the number of photos and the ADR (p-value = 0.000; p-value < 0.05) The correlation coefficient of 0.211 indicates that there is a weak, positive relationship between the two variables. Hence an increase in the number of photos, leads to an increase in ADR. The linear regression analysis shows that every additional photo is associated with a price increase of 0.08%.

More photos of the property enables the guest to better assess the apartment rooms, facilities and style and thus enables them to better know what to expect, which creates a sense of trust (Teubner et al., 2017). Besides trust, more pictures could also be an indication of greater professionalism of the hosts as more effort is put into the platform. In conclusion, these results confirm that hosts expect pictures are perceived to be important, since hosts who post more pictures charge a higher price Gibbs et al., 2017).

5. Conclusion

''How do characteristics of Airbnb listings in Rotterdam influence the price of Airbnb in Rotterdam?''

This study has examined the impact of a variety of variables on the rates published for Airbnb listings in Rotterdam in order to understand how Airbnb hosts set their prices and how perceptions of guests' willingness to pay for certain listing characteristics potentially influence their price decisions. The multiple regression analysis revealed that 9 of the 14 listing characteristics have a significant impact on the price, with listing type, overall rating and the cancellation policy causing the greatest price change.

The research model took into consideration the unique characteristics of the peer-to-peer platform and the attributes of hosts engaging in the sharing economy. It can be concluded that host characteristics have no significant effect on the price, as there is no difference in ADR between hosts with a superhost badge and hosts without a superhost badge, and professional hosts and non-professional hosts.

Moreover, the research study included traditional accommodation price determinants such as property characteristics. Most of these traditional listing characteristics greatly influence ADR, which suggests that Airbnb accommodation is very similar to traditional hotels and holiday apartments in multiple ways. Location and number of bedrooms and max number of guest are significantly correlated with the ADR. In line with findings of previous studies of traditional accommodation price determinants, a shorter distance from a focal point (the Town Hall of Rotterdam), can be associated with a higher ADR. Concretely, the linear regression analysis shows that every KM closer to the city center leads to a price markup of 5.11%. In addition, capacity is taken into account by Airbnb hosts. The number of bedrooms and the maximum number of guests tend to increase to getter, and both are positively related to price. In other words, apartments with more bedrooms can accommodate more guests, which significantly increases price.

Also, hosts charge a huge premium for privacy as private rooms were priced 40.68% lower than entire homes, and shared rooms were priced 61.20% lower than entire rooms. Furthermore host' experience influences price, as there is a positive relationship between the number of months that the listing is online on the platform and the ADR. However, a recently introduced tool: business ready status does not translate into price premiums.

With regards to rental rules, the instant booking tool does not impact price. However, there is a significant difference in ADR between the different cancellation policies. Flexible cancellation policies and lower prices are related, suggesting that hosts with a strict cancellation policy are driven by rational aspects rather than emotion, they set higher prices and want to secure their income by avoiding last-minute cancellations (Wang and Nicolau, 2017b).

Moreover, trust is crucial for the sharing economy accommodation rental as it helps to change a potential guests' interest into a booking request (Teubner et al., 2017; Bostman and Rogers, 2011; Hawlitschek et al., 2016; Ert et al., 2016) The entire process of selecting a listing and sending a booking request is conducted online, which makes the information showed on the Airbnb website the only reference point for potential guests (Hawlitschek et al., 2016). The different reputational tools implemented by Airbnb to facilitate trust between hosts and guests have been analyzed. While the number of bookings is not significantly correlated with price, a higher number of reviews are associated with a lower ADR.

Furthermore, a higher overall rating and more photos consistently translate into price premiums. Not surprisingly, higher star ratings are associated with higher prices. Hence, hosts tend to increase prices when they receive higher star ratings, which suggest that hosts expect guests to be willing to pay more for listings with a higher star rating. Also, the multiple linear regression analysis shows that the ADR increases with 0.08% with every additional photo.

In studying the networked hospitality market leader, this report has identified the price determinants of Airbnb listings in Rotterdam. The following hedonic model can be formulated, in which a unit increase in the listing characteristic represents a % increase in ADR.

$$Ln(ADR)_i = 3{,}645 + -0{,}051*DistanceTo + 0{,}074NumberOfBedrooms + -0{,}522Private + -0{,}947*Shared + 0{,}003*ListedMonths + 0{,}047*MaxGuests + 0{,}071*Moderate + 0{,}071*Strict + -0{,}001*NumberOfReviews + 0{,}095*OverallRating + 0{,}008*NumberOfPhotos + U_i$$

The study contributes to the few existing studies related to Airbnb and pricing as it explains which characteristics make up the price of a listing, and therefore indicates how Airbnb host set their prices and how they systematically link their prices to the characteristics of their listing.

6. Recommendations

6.1. Recommendations for Airbnb Hosts

Although no conclusions can be made about the efficiency of the pricing strategies of the Airbnb hosts, the following recommendations have been written for Airbnb hosts in Rotterdam willing to adjust their pricing strategy to other Airbnb hosts in Rotterdam.

The ADR could be increased when:

- The listing is an entire home or apartment
- The listing has a high overall star rating
- The listing has a moderate of strict cancellation policy
- The listing has more bedrooms
- The listing is located closer to the city center
- The listing accommodates more guests
- The listing has more photos
- The listing is listed longer on the platform
- The listing has less reviews

The listing characteristics have been listed based on the strength of the change in price caused by the listing characteristic.

6.2. Suggestions for further research

As mentioned in chapter 4, this research has various limitations due to time constraints and limited data availability. For this reason, the following suggestions for further research can be made:

- Research about the efficiency of host's pricing strategy by taking into account the demand side. This could be done by weighting the ADR by the occupancy rate.
- Research about the influence of seasons, special events and moments of the week (weekdays vs. weekends) on the price by using multiple price points.
- Research the influence of other listing characteristics such as amenities and services, market competition and other external factors.
- Investigate price differences between different target groups, such as business travelers vs. leisure travelers.
- Research the price effects of the listings variables for various price ranges by applying interquartile ranges of the ADR.
- Test the influence of other focal points in Rotterdam, such as the harbor or prices in different neighborhoods.
- Investigate psychological and social factors that might influence the pricing strategies of Airbnb hosts.

7. References

Airbnb, 2017a, *About Us - Airbnb* Available at: https://www.airbnb.com/about/about-us (Accessed 30 November 2017).

Airbnb, 2017b, *Airbnb Cancellation Policies* Available at: https://www.airbnb.com/home/cancellation_policies (Accessed 14 January 2018).

Airbnb, 2017c, *Airbnb Superhost* Available at: https://www.airbnb.com/superhost (Accessed 14 January 2018).

Airbnb, 2017d, *How do star ratings work? | Airbnb Help Center* Available at: https://www.airbnb.com/help/article/1257/how-do-star-ratings-work (Accessed 14 January 2018).

Airbnb, 2017e, *Rent Out Your House, Apartment or Room on Airbnb (2018)* Available at: https://www.airbnb.com/host/homes (Accessed 14 January 2018).

Airbnb, 2017f, *What do the different room types mean? | Airbnb Help Center* Available at: https://www.airbnb.com/help/article/317/what-do-the-different-room-types-mean (Accessed 14 January 2018).

Airbnb, 2017g, *What is Instant Book? | Airbnb Help Center* Available at: https://www.airbnb.com/help/article/523/what-is-instant-book (Accessed 14 January 2018).

Airbnb, 2017h, *What makes a listing Business Travel Ready? | Airbnb Help Center* Available at: https://www.airbnb.com/help/article/1185/what-makes-a-listing-business-travel-ready (Accessed 14 January 2018).

AirDNA, 2017, *Airbnb Data | AirBNB Analytics | AirDNA* Available at: https://www.airdna.co/ (Accessed 28 August 2017).

Balck, B. and Cracau, D., 2015 *Empirical analysis of customer motives in the shareconomy: a cross-sectoral comparison*,

Becerra, M., Santalo, J. and Silva, R., 2011, *Being better vs. being different: Differentiation, competition, and pricing strategies in the Spanish hotel industry* Available at: https://pdfs.semanticscholar.org/e310/96709b02a85d9dee61785b921903d1196bf8.pdf (Accessed 27 September 2017).

Bostman, R. and Rogers, R., 2011 *What's Mine Is Yours: How Collaborative Consumption is Changing the Way We Live by Rachel Botsman*, 0 edition., HarperCollins Business.

Cambridge Dictionary, 2017 Definition characteristic. Available at: https://dictionary.cambridge.org/dictionary/english/characteristic.

Carson, B., 2016, *How 3 guys turned renting an air mattress in their apartment into a $25 billion company* Available at: http://www.businessinsider.com/how-airbnb-was-founded-a-visual-history-2016-2 (Accessed 1 December 2017).

Chen, C.-F. and Rothschild, R., 2010 An application of hedonic pricing analysis to the case of hotel rooms in Taipei. *Tourism Economics*, 16, pp.0–0.

Coenders, G., Espinet, J.M. and Saez, M., 2013 *Predicting random level and seasonsanlity of hotel prices: A latent growth curve approach*, Edelman, B. and Luca, M., 2014 *Digital Discrimination: The Case of Airbnb.com*, Harvard Business School.

Ert, E., Fleischer, A. and Magen, N., 2016 Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management*, 55(Supplement C), pp.62–73.

Fleischer, A., 2012 A room with a view—A valuation of the Mediterranean Sea view. *Tourism Management*, 33(3), pp.598–602.

Gebbia, J., 2016 *How Airbnb designs for trust*,

Gemeente Rotterdam, 2017, *Wijkprofiel Rotterdam* Available at: http://wijkprofiel.rotterdam.nl/nl/2018/rotterdam (Accessed 14 January 2018).

Gibbs, C. et al., 2017 *Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings*,

Glez-Peña, D. et al., 2013 Web scraping technologies in an API world. *Briefings in bioinformatics*, 15.

Guinby, D. and Gasdia, M., 2014 *Share this! Private accommodation and the rise of the new gen renters*,

Gutt, D. and Herrmann, P., 2015 *Sharing means caring? Hosts' price reaction to rating visibility*,

Guttentag, D., 2015, *Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector* Available at: http://studenten.tudelft.nl/fileadmin/Files/studentenportal/os/BKspecifiek/Workshops/Airbnb_disruptive_innovation_and_the_rise_of_an_informal_tourism_accommodation_sector.pdf (Accessed 13 November 2017).

Hamari, J., Ukkonen, A. and Sjoklint, M., 2015, *The Sharing Economy: Why People Participate in Collaborative Consumption (PDF Download Available)* Available at: https://www.researchgate.net/publication/255698095_The_Sharing_Economy_Why_People_Participate_in_Collaborative_Consumption (Accessed 30 November 2017).

Hawlitschek, F., Teubner, T. and Weinhardt, C., 2016 Trust in the Sharing Economy. *Die Unternehmung – Swiss Journal of Business Research and Practice*, 70, pp.26–44.

Heo, C.Y., 2016 Sharing economy and prospects in tourism research. *Annals of Tourism Research*, 58(Supplement C), pp.166–170.

Hill, D., 2015 How Much Is Your Spare Room Worth? *Spectrum, IEEE*, 52, pp.32–58.

Hotelschool The Hague, 2017, *About the Research Centre* Available at: https://hotelschool.nl/en/research/about-research-centre (Accessed 10 January 2018).

Hung, W.-T., Shang, J.-K. and Wang, F.-C., 2010 Pricing determinants in the hotel industry: Quantile regression analysis. *International Journal of Hospitality Management*, 29(3), pp.378–384.

Ikkala, T. and Lampinen, A., 2014a *Defining the price of hospitality: Networked hospitality exchange via Airbnb*,

Ikkala, T. and Lampinen, A., 2014b Defining the price of hospitality: networked hospitality exhange via Airbnb.

Ikkala, T. and Lampinen, A., 2015 *Monetizing Network in Hospitality: Hospitality and Sociability in the Context of Airbnb*,

Juaneda, C., Raya, J.M. and Sastre, F., 2011 Pricing the time and location of a stay at a hotel or apartment. *Tourism Economics*, 17, pp.321–338.

Kakar, V., Voelz, J., Wu, J. and Franco, J., 2017 The Visible Host: Does race guide Airbnb rental rates in San Francisco? *Journal of Housing Economics*. Available at: http://www.sciencedirect.com/science/article/pii/S1051137716301309 (Accessed 1 December 2017).

Kaplan, A. and Haenlein, M., 2009, *Users of the world, unite! The challenges and opportunities of Social Media* Available at: https://ac.els-cdn.com/S0007681309001232/1-s2.0-S0007681309001232-main.pdf?_tid=77292b9c-d434-11e7-a6ec-00000aab0f6b&acdnat=1511870926_729a20638ad1d59fd744898691cf167d (Accessed 28 November 2017).

Lamberton, C., 2015, *Collaborative consumption: a goal-based framework* Available at: https://ac.els-cdn.com/S2352250X15003115/1-s2.0-S2352250X15003115-main.pdf?_tid=213d3b0e-d436-11e7-856f-00000aacb35d&acdnat=1511871641_4195381872c714a3cdb7f2739f5bed07 (Accessed 28 November 2017).

Lampinen, A. and Cheshire, C., 2016, *Hosting via Airbnb: MOtivations and Financial Assurances in Monetized Netwrok Hospitality* Available at: http://www.mobilelifecentre.org/sites/default/files/Airbnb%20Submitted%20Camera.pdf (Accessed 28 November 2017).

Li, J., Moreno, A. and Zhang, D., 2015 Agent Behavior in the Sharing Economy: Evidence from Airbnb. *SSRN Electronic Journal*.

Liang, S., Schuckert, M., Law, R. and Chen, C.-C., 2017 Be a "Superhost": The importance of badge systems for peer-to-peer rental accommodations. *Tourism Management*, 60(Supplement C), pp.454–465.

Nowak, B. et al., 2015 *Global Insight: Who Will Airbnb Hurt More – Hotels or OTAs?*,

Oskam, J., 2016, *Airbnb or "Networked Hospitality Business": Between Innovation andCommercialization. A Research Agenda* Available at: http://ka-au.net/wp-content/uploads/2017/01/03.RESERACH_HOSPITALITY02_NEUTRAL_ENG.pdf (Accessed 24 July 2017).

PWC, 2015, *Spotlight on the sharing economy* Available at: https://www.pwc.com/us/en/advisory-services/publications/consumer-intelligence-series/sharing-economy.html (Accessed 13 November 2017).

Rosen, S., 1974 *Hedonic Prices and Implicit Markets: Product Differentiation and Pure Competition*,

Saló, A. and Garriga, A., 2011 The Second-Home Rental Market: A Hedonic Analysis of the Effect of Different Characteristics and a High-Market-Share Intermediary on Price. *Tourism Economics*, 17(5), pp.1017–1033.

Schamel, G., 2012 Weekend vs. midweek stays: modelling hotel room rates in a small market.

International Journal of Hospitality Management, 31(4), pp.1113–1118.

Statistics Solutions, 2017 *Assumptions of Multiple Linear Regression*,

Stats, 2011 *Multiple Regression - SPSS*,

Sundararajan, A., 2016 *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism*, Cambridge, Massachusetts, The MIT Press.

Tabachnick and Fidell, 2007, *School of Psychology - University of Queensland* Available at: https://psychology.uq.edu.au/?file=1505 (Accessed 11 December 2017).

Te Grotenhuis, M. and Thijs, P., 2012 *Dummy variables and their interactions in regression analysis: examples from research on body mass index*, Radboud University Nijmegen.

Teubner, T., Hawlitschek, F. and Dann, D., 2017 *Price Determinants on Airbnb: How reputation pays off in the sharing economy*,

Thrane, C., 2007 Examining the determinants of room rates for hotels in capital cities: The Oslo experience. *Journal of Revenue & Pricing Management*, 5.

Tussyadiah, I., 2014 An Exploratory Study on Drivers and Deterrents of Collaborative Consumption in Travel. In: pp. 817–830.

Tussyadiah, I. and Pesonen, J., 2015 Impacts of Peer-to-Peer Accommodation Use on Travel Patterns. *Journal of Travel Research*.

Wang, D. and Nicolau, J.L., 2017a *Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com*,

Wang, D. and Nicolau, J.L., 2017b Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. *International Journal of Hospitality Management*, 62(Supplement C), pp.120–131.

White, P.J. and Mulligan, G.F., 2002 Hedonic Estimates of Lodging Rates in the Four Corners Region. *The Professional Geographer*, 54(4), pp.533–543.

Xie, K. and Mao, Z., 2017 *The impacts of quality and quantity attributes of Airbnb hosts on listing performance*,

Yang, Y., Mueller, N.J. and Croes, R.R., 2016 Market accessibility and hotel prices in the Caribbean: The moderating effect of quality-signaling factors. *Tourism Management*, 56(Supplement C), pp.40–51.

Yoo, M., Lee, S.J. and Bai, B., 2011 Hospitality marketing research from 2000 to 2009: Topics, methods, and trends. *International Journal of Contemporary Hospitality Management*, 23, pp.517–532.

Zervas, G., Proserpio, D. and Byers, J., 2016, *The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry* Available at:

http://people.bu.edu/zg/publications/airbnb.pdf (Accessed 13 November 2017).

Zhang, H. et al., 2011 Modeling hotel room price with geographically weighted regression. *International Journal of Hospitality Management*, 30(4), pp.1036–1043.

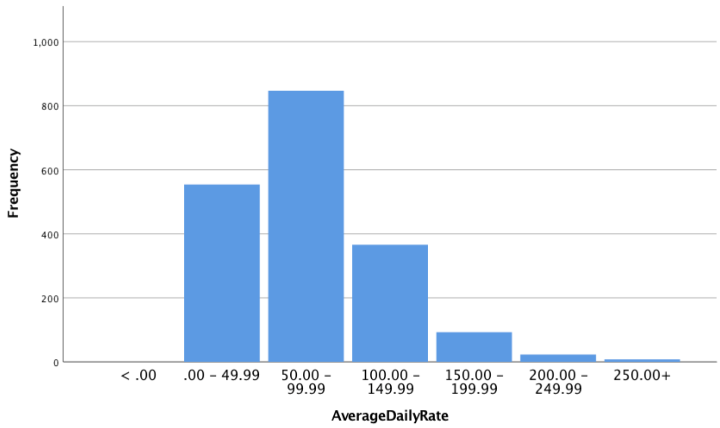
8. Appendices

8.1. Descriptive Statistics

Test 1: Descriptive statistics ADR	
Variable	ADR
Level of measurement	Scale

AverageDailyRate (Binned)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00 - 49.99	554	29.3	29.3	29.3
	50.00 - 99.99	847	44.8	44.8	74.1
	100.00 - 149.99	366	19.4	19.4	93.4
	150.00 - 199.99	93	4.9	4.9	98.4
	200.00 - 249.99	23	1.2	1.2	99.6
	250.00+	8	.4	.4	100.0
	Total	1891	100.0	100.0	



Statistics

AverageDailyRate

N	Valid	1891
	Missing	0
Mean		78.6224
Median		70.8300
Mode		34.00
Std. Deviation		42.40681
Variance		1798.338
Range		261.67
Minimum		10.00
Maximum		271.67
Percentiles	25	46.7800
	50	70.8300
	75	101.5000

Interpretation

The ADR ranges €10.00 to €261.67. On average the ADR is €78.62. Most listing prices range between €50.00 – €99.99 (44.8%).

Test 2: Descriptive statistics superhost badge	
Variable	Superhost badge
Level of measurement	Nominal
Codebook	Yes = 1 No = 0

Statistics

Superhost

N	Valid	1703
	Missing	188
Mode		0
Minimum		0
Maximum		1

Superhost

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	1579	83.5	92.7	92.7
	1	124	6.6	7.3	100.0
	Total	1703	90.1	100.0	
Missing	System	188	9.9		
Total		1891	100.0		

Interpretation

Of the 1891listings, the data set provides available data for 1703 listings about the superhost status. The mode (0) reveals that most hosts do not have a superhost badge. More specifically, of the 1703 listings, 1779 hosts do not have a superhost badge (92.72%) and only 124 hosts do have a superhost badge (7.28%).

Test 3: Descriptive statistics number of listings	
Variable	Number of listings
Level of measurement	Scale

Statistics

NumberOfListings

N	Valid	1891
	Missing	0
Mean		2.44
Median		1.00
Mode		1
Std. Deviation		3.981
Variance		15.851
Range		36
Minimum		1
Maximum		37
Sum		4610
Percentiles	25	1.00
	50	1.00
	75	2.00

NumberOfListings

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1158	61.2	61.2	61.2
	2	299	15.8	15.8	77.0
	3	179	9.5	9.5	86.5
	4	82	4.3	4.3	90.9
	5	28	1.5	1.5	92.3
	6	37	2.0	2.0	94.3
	7	7	.4	.4	94.7
	8	21	1.1	1.1	95.8
	9	8	.4	.4	96.2
	10	1	.1	.1	96.2
	11	6	.3	.3	96.6
	12	15	.8	.8	97.4
	13	6	.3	.3	97.7
	14	9	.5	.5	98.1
	15	5	.3	.3	98.4
	16	13	.7	.7	99.1
	20	2	.1	.1	99.2
	37	15	.8	.8	100.0
	Total	1891	100.0	100.0	

Interpretation

The number of listings ranges from 1 listing to 37 listings. On average, hosts have 2.44 listings. However, the mode reveals that most hosts (1158) have only 1 listing (61.2%).

Test 4: Descriptive statistics distance to the city center	
Variable	Distance to the city center
Level of measurement	Scale

DistanceTo

N	Valid	1891
	Missing	0
Mean		1.968360
Median		1.605966
Mode		.0597[a]
Std. Deviation		1.4339276
Variance		2.056
Range		10.7410
Minimum		.0597
Maximum		10.8007
Sum		3722.1679
Percentiles	25	1.041296
	50	1.605966
	75	2.392422

a. Multiple modes exist. The smallest value is shown

Interpretation

The distance to the city center ranges from 0,06 KM till 10.8 KM. On average, the distance to the city center is 1.97 KM.

Test 5: Descriptive statistics number of bedrooms	
Variable	*Number of bedrooms*
Level of measurement	*Scale*

Bedrooms

N	Valid	1889
	Missing	2
Mean		1.32
Median		1.00
Mode		1
Std. Deviation		.756
Variance		.572
Range		10
Minimum		0
Maximum		10
Sum		2488
Percentiles	25	1.00
	50	1.00
	75	2.00

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	80	4.2	4.2	4.2
	1	1290	68.2	68.3	72.5
	2	405	21.4	21.4	94.0
	3	89	4.7	4.7	98.7
	4	17	.9	.9	99.6
	5	3	.2	.2	99.7
	6	1	.1	.1	99.8
	7	2	.1	.1	99.9
	8	1	.1	.1	99.9
	10	1	.1	.1	100.0
	Total	1889	99.9	100.0	
Missing	System	2	.1		
Total		1891	100.0		

Interpretation

The number of bedrooms ranges from 0 to 10. The mode (1) reveals that most listings boast one bedroom (68.3%). Also many listings boast two bedrooms (21.4%).

Test 6: Descriptive statistics listing type	
Variable	Listing type
Level of measurement	Nominal
Code book	Entire home / apartment = 2 Private room = 1 Shared room = 0

Statistics

ListingType

N	Valid	1891
	Missing	0
Median		2.00
Mode		2
Range		2
Minimum		0
Maximum		2
Percentiles	25	1.00
	50	2.00
	75	2.00

ListingType

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	43	2.3	2.3	2.3
	1	652	34.5	34.5	36.8
	2	1196	63.2	63.2	100.0
	Total	1891	100.0	100.0	

Interpretation

The descriptive statistics illustrate that most Airbnb listings in Rotterdam are an entire home / apartment (n = 1196, 63.25%), followed by private rooms (n = 652, 34.48%) and only 43 listings (2.27%) of Airbnb listings are a shared room.

Test 7: Descriptive statistics business ready status	
Variable	Business ready
Level of measurement	Nominal

Statistics

BusinessReady

N	Valid	1891
	Missing	0
Mode		0
Minimum		0
Maximum		1

BusinessReady

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	1650	87.3	87.3	87.3
	1	241	12.7	12.7	100.0
	Total	1891	100.0	100.0	

Interpretation

The descriptive statistics reveal that most listings are not business ready (n = 1650, 87.26%) and only few listings (n= 241, 12.74%) are business ready.

Test 8: Descriptive statistics days existing	
Variable	Days existing
Level of measurement	Scale

Statistics

ListedMonths

N	Valid	1891
	Missing	0
Mean		26.69
Median		23.00
Mode		18
Std. Deviation		12.956
Variance		167.866
Range		84
Minimum		11
Maximum		95
Percentiles	25	18.00
	50	23.00
	75	32.00

Interpretation

he days of existence of the Airbnb range from 11 months till 95 months. On average the listings exists 27 months (26.69).

Test 9: Descriptive statistics max number of guests

Variable	Max number of guests
Level of measurement	Scale

Statistics

MaxGuests

N	Valid	1891
	Missing	0
Mean		2.87
Median		2.00
Mode		2
Std. Deviation		1.672
Variance		2.796
Range		15
Minimum		1
Maximum		16
Percentiles	25	2.00
	50	2.00
	75	4.00

MaxGuests

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	179	9.5	9.5	9.5
	2	949	50.2	50.2	59.7
	3	217	11.5	11.5	71.1
	4	333	17.6	17.6	88.7
	5	69	3.6	3.6	92.4
	6	97	5.1	5.1	97.5
	7	13	.7	.7	98.2
	8	18	1.0	1.0	99.2
	9	3	.2	.2	99.3
	10	4	.2	.2	99.5
	12	3	.2	.2	99.7
	14	1	.1	.1	99.7
	16	5	.3	.3	100.0
	Total	1891	100.0	100.0	

Interpretation

The maximum number of guests ranges between 1 and 16 guest. The mode (2) reveals that most Airbnb hosts allow two guests in their listing (50.2%). On average, Airbnb hosts allow 3 (2.87) guests in their listing.

Test 10: Descriptive statistics cancellation policy	
Variable	Cancellation policy
Level of measurement	Ordinal
Code book	Flexible = 2 Moderate = 1 Strict = 0

Statistics

CancellationPolicy

N	Valid	1891
	Missing	0
Median		1.00
Mode		2
Variance		.641
Range		2
Minimum		0
Maximum		2
Percentiles	25	1.00
	50	1.00
	75	2.00

CancellationPolicy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	438	23.2	23.2	23.2
	1	578	30.6	30.6	53.7
	2	875	46.3	46.3	100.0
	Total	1891	100.0	100.0	

Interpretation

Of all the Airbnb listings, 875 listings offer a flexible cancellation policy (46.3%), 578 listings offer a moderate cancellation policy (30.6%) and 438 offer a strict cancellation policy (23.2%).

Test 11: Descriptive statistics Instantbook enabled	
Variable	Instantbook enabled
Level of measurement	Nominal
Code book	Yes = 1 No = 0

Statistics

InstantbookEnabled

N	Valid	1891
	Missing	0
Mode		0
Minimum		0
Maximum		1

InstantbookEnabled

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	1606	84.9	84.9	84.9
	1	285	15.1	15.1	100.0
	Total	1891	100.0	100.0	

Interpretation

Of the 1891 listings, 1606 listings do not have instant booking enabled (84.93%) and 285 listings do have instant booking enabled (15.07%). Hence, most listings do not have Instant booking enabled (mode).

Test 12: Descriptive statistics number of bookings	
Variable	Number of bookings
Level of measurement	Scale

Statistics

NumberofBookingsLTM

N	Valid	1891
	Missing	0
Mean		16.45
Median		7.00
Mode		1
Std. Deviation		23.946
Variance		573.426
Range		195
Minimum		0
Maximum		195
Percentiles	25	3.00
	50	7.00
	75	20.00

Interpretation

The number of bookings of the last twelve months range from 0 bookings till 195 bookings. On average the listings have been booked 16.45 times. However, most listings have only been booked once in the last twelve months (14.3%).

Test 13: Descriptive statistics number of reviews	
Variable	Number of reviews

Level of measurement	Scale

Statistics

NumberofReviews

N	Valid	1891
	Missing	0
Mean		12.94
Median		4.00
Mode		0
Std. Deviation		25.659
Variance		658.408
Range		299
Minimum		0
Maximum		299
Percentiles	25	1.00
	50	4.00
	75	12.00

Interpretation

The number of reviews ranges from 0 reviews till 299 reviews. On average the 1981 listings have 12.94 reviews. However, most listings have zero reviews (21%).

Test 14: Descriptive statistics overall rating

Variable	Overall rating
Level of measurement	Scale

Statistics

OverallRating

N	Valid	1453
	Missing	438
Mean		4.5635
Median		4.7000
Mode		5.00
Std. Deviation		.47705
Variance		.228
Range		4.00
Minimum		1.00
Maximum		5.00
Percentiles	25	4.4000
	50	4.7000
	75	4.9000

OverallRating

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	5	.3	.3	.3
	2.00	3	.2	.2	.6
	2.50	3	.2	.2	.8
	2.60	1	.1	.1	.8
	2.90	1	.1	.1	.9
	3.00	19	1.0	1.3	2.2
	3.20	2	.1	.1	2.3
	3.40	3	.2	.2	2.5
	3.50	15	.8	1.0	3.6
	3.60	6	.3	.4	4.0
	3.80	8	.4	.6	4.5
	3.90	11	.6	.8	5.3
	4.00	124	6.6	8.5	13.8
	4.10	5	.3	.3	14.2
	4.20	68	3.6	4.7	18.9
	4.30	73	3.9	5.0	23.9
	4.40	44	2.3	3.0	26.9
	4.50	209	11.1	14.4	41.3
	4.60	65	3.4	4.5	45.8
	4.70	167	8.8	11.5	57.3
	4.80	233	12.3	16.0	73.3
	4.90	66	3.5	4.5	77.8
	5.00	322	17.0	22.2	100.0
	Total	1453	76.8	100.0	
Missing	System	438	23.2		
Total		1891	100.0		

Interpretation

Of the 1891 listings, overall rating data is only scrapped for 1453 listings. The overall rating ranges from 1 star till 5 stars. On average the listings have a 4.56 star rating. Most listings have a 5 star rating (22.2%).

Test 15: Descriptive statistics number of photo's

Variable	*Number of photo’s*
Level of measurement	*Scale*

Statistics

NumberofPhotos

N	Valid	1891
	Missing	0
Mean		14.14
Median		12.00
Mode		8
Std. Deviation		10.690
Variance		114.284
Range		150
Minimum		1
Maximum		151
Percentiles	25	7.00
	50	12.00
	75	18.00

Interpretation

The number of photo’s ranges from 1 photo till 150 photo’s. On average the listings have 14.4 photos. However, most listings have 8 photo’s.

8.2. Multiple Regression Analysis

The following tables present the outcome of the multiple regression analysis in SPSS (stepwise method)

SUMMARY VARIABLES

	Mean	Std. Deviation	N
LogADR	4,2499	0,51937	1370
Superhost	0,09	0,282	1370
Professional	0,4015	0,49037	1370
NumberofBedrooms	1,33	0,770	1370
DistanceTo	1,930283	1,4067907	1370
Shared	0,0219	0,14640	1370
Private	0,3255	0,46875	1370
BusinessReady	0,10	0,303	1370
MaxGuests	2,97	1,731	1370
Moderate	0,3445	0,47539	1370
Strict	0,2620	0,43991	1370
ListedMonths	28,25	13,708	1370
InstantbookEnabled	0,15	0,361	1370
NumberOfBookingsLTM	21,21	26,425	1370
NumberOfReviews	17,32	28,756	1370
OverallRating	4,5704	0,47403	1370
NumberofPhotos	15,59	11,123	1370

TABLE 6 Summary Variables Multiple Regression Analysis

CORRELATIONS MATRIX

Correlations

		LogADR	Superhost	Professional	NumberofBedrooms	DistanceTo	Shared	Private	BusinessReady	MaxGuests	Moderate	Strict	ListedMonths	InstantbookEnabled	NumberOfBookingsLTM	NumberOfReviews	OverallRating	NumberofPhotos
Pearson Correlation	LogADR	1,000	0,032	-0,125	0,409	-0,195	-0,234	-0,606	0,016	0,429	0,053	0,188	0,132	-0,026	-0,028	-0,011	0,131	0,386
	Superhost	0,032	1,000	0,006	-0,011	-0,033	-0,046	0,051	0,050	-0,035	0,038	0,040	0,115	0,019	0,195	0,268	0,159	0,114
	Professional	-0,125	0,006	1,000	-0,037	0,047	0,020	0,210	-0,016	0,069	-0,080	0,061	0,114	0,005	0,086	0,040	-0,120	0,024
	NumberofBedrooms	0,409	-0,011	-0,037	1,000	0,096	-0,064	-0,293	-0,028	0,699	-0,003	0,157	0,030	-0,030	0,028	0,007	-0,012	0,224
	DistanceTo	-0,195	-0,033	0,047	0,096	1,000	0,023	0,106	-0,030	0,043	-0,025	0,004	-0,031	0,006	-0,015	-0,030	-0,080	-0,060
	Shared	-0,234	-0,046	0,020	-0,064	0,023	1,000	-0,104	0,015	0,083	-0,056	-0,044	-0,005	-0,036	0,013	-0,020	-0,025	-0,076
	Private	-0,606	0,051	0,210	-0,293	0,106	-0,104	1,000	-0,054	-0,384	-0,002	-0,124	-0,032	0,023	0,071	0,049	-0,046	-0,231
	BusinessReady	0,016	0,050	-0,016	-0,028	-0,030	0,015	-0,054	1,000	-0,004	0,024	0,040	-0,013	0,063	0,026	0,037	-0,010	0,049
	MaxGuests	0,429	-0,035	0,069	0,699	0,043	0,083	-0,384	-0,004	1,000	-0,047	0,194	0,080	0,001	0,099	0,054	-0,097	0,241
	Moderate	0,053	0,038	-0,080	-0,003	-0,025	-0,056	-0,002	0,024	-0,047	1,000	-0,432	0,052	-0,024	0,131	0,090	0,068	-0,001
	Strict	0,188	0,040	0,061	0,157	0,004	-0,044	-0,124	0,040	0,194	-0,432	1,000	0,096	-0,020	-0,015	0,020	-0,018	0,204
	ListedMonths	0,132	0,115	0,114	0,030	-0,031	-0,005	-0,032	-0,013	0,080	0,052	0,096	1,000	-0,106	0,102	0,332	0,019	0,201
	InstantbookEnabled	-0,026	0,019	0,005	-0,030	0,006	-0,036	0,023	0,063	0,001	-0,024	-0,020	-0,106	1,000	0,227	0,180	-0,071	0,002
	NumberOfBookingsLTM	-0,028	0,195	0,086	0,028	-0,015	0,013	0,071	0,026	0,099	0,131	-0,015	0,102	0,227	1,000	0,729	0,075	0,185
	NumberOfReviews	-0,011	0,268	0,040	0,007	-0,030	-0,020	0,049	0,037	0,054	0,090	0,020	0,332	0,180	0,729	1,000	0,062	0,192
	OverallRating	0,131	0,159	-0,120	-0,012	-0,080	-0,025	-0,046	-0,010	-0,097	0,068	-0,018	0,019	-0,071	0,075	0,062	1,000	0,128
	NumberofPhotos	0,386	0,114	0,024	0,224	-0,060	-0,076	-0,231	0,049	0,241	-0,001	0,204	0,201	0,002	0,185	0,192	0,128	1,000
Sig. (1-tailed)	LogADR		0,115	0,000	0,000	0,000	0,000	0,000	0,281	0,000	0,024	0,000	0,000	0,168	0,153	0,342	0,000	0,000
	Superhost	0,115		0,405	0,346	0,112	0,044	0,029	0,032	0,098	0,079	0,069	0,000	0,239	0,000	0,000	0,000	0,000
	Professional	0,000	0,405		0,086	0,040	0,231	0,000	0,280	0,005	0,002	0,013	0,000	0,422	0,001	0,072	0,000	0,191
	NumberofBedrooms	0,000	0,346	0,086		0,000	0,009	0,000	0,146	0,000	0,459	0,000	0,133	0,133	0,147	0,395	0,328	0,000
	DistanceTo	0,000	0,112	0,040	0,000		0,202	0,000	0,130	0,055	0,177	0,434	0,128	0,417	0,287	0,133	0,001	0,013
	Shared	0,000	0,044	0,231	0,009	0,202		0,000	0,285	0,001	0,019	0,053	0,428	0,090	0,313	0,235	0,174	0,003
	Private	0,000	0,029	0,000	0,000	0,000	0,000		0,022	0,000	0,468	0,000	0,116	0,198	0,004	0,034	0,043	0,000
	BusinessReady	0,281	0,032	0,280	0,146	0,130	0,285	0,022		0,445	0,186	0,069	0,317	0,010	0,171	0,087	0,350	0,036
	MaxGuests	0,000	0,098	0,005	0,000	0,055	0,001	0,000	0,445		0,042	0,000	0,002	0,492	0,000	0,022	0,000	0,000
	Moderate	0,024	0,079	0,002	0,459	0,177	0,019	0,468	0,186	0,042		0,000	0,026	0,185	0,000	0,000	0,006	0,481
	Strict	0,000	0,069	0,013	0,000	0,434	0,053	0,000	0,069	0,000	0,000		0,000	0,233	0,289	0,234	0,248	0,000
	ListedMonths	0,000	0,000	0,000	0,133	0,128	0,428	0,116	0,317	0,002	0,026	0,000		0,000	0,000	0,000	0,243	0,000
	InstantbookEnabled	0,168	0,239	0,422	0,133	0,417	0,090	0,198	0,010	0,492	0,185	0,233	0,000		0,000	0,000	0,004	0,470
	NumberOfBookingsLTM	0,153	0,000	0,001	0,147	0,287	0,313	0,004	0,171	0,000	0,000	0,289	0,000	0,000		0,000	0,003	0,000
	NumberOfReviews	0,342	0,000	0,072	0,395	0,133	0,235	0,034	0,087	0,022	0,000	0,234	0,000	0,000	0,000		0,011	0,000
	OverallRating	0,000	0,000	0,000	0,328	0,001	0,174	0,043	0,350	0,000	0,006	0,248	0,243	0,004	0,003	0,011		0,000
	NumberofPhotos	0,000	0,000	0,191	0,000	0,013	0,003	0,000	0,036	0,000	0,481	0,000	0,000	0,470	0,000	0,000	0,000	
N	LogADR	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	Superhost	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	Professional	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	NumberofBedrooms	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	DistanceTo	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	Shared	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	Private	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	BusinessReady	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	MaxGuests	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	Moderate	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	Strict	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	ListedMonths	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	InstantbookEnabled	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	NumberOfBookingsLTM	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	NumberOfReviews	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	OverallRating	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370
	NumberofPhotos	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370	1370

TABLE 7 Correlation Matrix Multiple Regression Analysis

VARIABLES INCLUDED

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Private		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Shared		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	MaxGuests		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	NumberofPhotos		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
5	DistanceTo		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
6	OverallRating		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
7	NumberofBedrooms		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
8	ListedMonths		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
9	NumberOfReviews		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
10	Moderate		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
11	Strict		Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: LogADR

TABLE 8 Variables Included in Multiple Regression Analysis

MODEL SUMMARY

Model Summary[l]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.606[a]	0,368	0,367	0,41310	
2	.676[b]	0,457	0,456	0,38289	
3	.713[c]	0,509	0,508	0,36437	
4	.737[d]	0,543	0,542	0,35143	
5	.749[e]	0,561	0,560	0,34465	
6	.754[f]	0,569	0,567	0,34163	
7	.759[g]	0,576	0,573	0,33922	
8	.761[h]	0,579	0,577	0,33788	
9	.764[i]	0,584	0,581	0,33620	
10	.765[j]	0,585	0,582	0,33574	
11	.767[k]	0,588	0,585	0,33473	1,188

a. Predictors: (Constant), Private

b. Predictors: (Constant), Private, Shared

c. Predictors: (Constant), Private, Shared, MaxGuests

d. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos

e. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo

f. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating

g. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms

h. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths

i. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews

j. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews, Moderate

k. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews, Moderate, Strict

l. Dependent Variable: LogADR

TABLE 9 Model Summary Multiple Regression Analysis

ANOVA TEST

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	135,820	1	135,820	795,879	.000[b]
	Residual	233,454	1368	0,171		
	Total	369,274	1369			
2	Regression	168,865	2	84,432	575,916	.000[c]
	Residual	200,410	1367	0,147		
	Total	369,274	1369			
3	Regression	187,913	3	62,638	471,780	.000[d]
	Residual	181,362	1366	0,133		
	Total	369,274	1369			
4	Regression	200,689	4	50,172	406,233	.000[e]
	Residual	168,586	1365	0,124		
	Total	369,274	1369			
5	Regression	207,254	5	41,451	348,963	.000[f]
	Residual	162,020	1364	0,119		
	Total	369,274	1369			
6	Regression	210,201	6	35,033	300,180	.000[g]
	Residual	159,073	1363	0,117		
	Total	369,274	1369			
7	Regression	212,549	7	30,364	263,876	.000[h]
	Residual	156,725	1362	0,115		
	Total	369,274	1369			
8	Regression	213,901	8	26,738	234,209	.000[i]
	Residual	155,374	1361	0,114		
	Total	369,274	1369			
9	Regression	215,556	9	23,951	211,900	.000[j]
	Residual	153,718	1360	0,113		
	Total	369,274	1369			
10	Regression	216,088	10	21,609	191,703	.000[k]
	Residual	153,187	1359	0,113		
	Total	369,274	1369			
11	Regression	217,116	11	19,738	176,159	.000[l]
	Residual	152,158	1358	0,112		
	Total	369,274	1369			

a. Dependent Variable: LogADR

b. Predictors: (Constant), Private

c. Predictors: (Constant), Private, Shared

d. Predictors: (Constant), Private, Shared, MaxGuests

e. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos

f. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo

g. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating

h. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms

i. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths

j. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews

k. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews, Moderate

l. Predictors: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews, Moderate, Strict

TABLE 10 Anova Test Multiple Regression Analysis

STEPWISE MODELS INCLUDED VARIABLES

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	4,469	0,014		328,820	0,000	4,442	4,495					
	Private	-0,672	0,024	-0,606	-28,211	0,000	-0,719	-0,625	-0,606	-0,606	-0,606	1,000	1,000
2	(Constant)	4,503	0,013		351,664	0,000	4,478	4,528					
	Private	-0,707	0,022	-0,638	-31,833	0,000	-0,750	-0,663	-0,606	-0,652	-0,634	0,989	1,011
	Shared	-1,067	0,071	-0,301	-15,013	0,000	-1,206	-0,928	-0,234	-0,376	-0,299	0,989	1,011
3	(Constant)	4,251	0,024		174,711	0,000	4,203	4,299					
	Private	-0,603	0,023	-0,544	-26,427	0,000	-0,648	-0,558	-0,606	-0,582	-0,501	0,847	1,180
	Shared	-1,105	0,068	-0,312	-16,326	0,000	-1,238	-0,973	-0,234	-0,404	-0,310	0,987	1,013
	MaxGuests	0,074	0,006	0,246	11,978	0,000	0,062	0,086	0,429	0,308	0,227	0,851	1,175
4	(Constant)	4,127	0,026		156,103	0,000	4,075	4,179					
	Private	-0,566	0,022	-0,511	-25,362	0,000	-0,610	-0,522	-0,606	-0,566	-0,464	0,825	1,213
	Shared	-1,030	0,066	-0,290	-15,670	0,000	-1,159	-0,901	-0,234	-0,390	-0,287	0,974	1,026
	MaxGuests	0,063	0,006	0,210	10,438	0,000	0,051	0,075	0,429	0,272	0,191	0,824	1,213
	NumberofPhotos	0,009	0,001	0,195	10,171	0,000	0,007	0,011	0,386	0,265	0,186	0,907	1,102
5	(Constant)	4,209	0,028		149,490	0,000	4,154	4,264					
	Private	-0,545	0,022	-0,492	-24,729	0,000	-0,589	-0,502	-0,606	-0,556	-0,444	0,812	1,232
	Shared	-1,018	0,064	-0,287	-15,796	0,000	-1,145	-0,892	-0,234	-0,393	-0,283	0,974	1,027
	MaxGuests	0,067	0,006	0,225	11,317	0,000	0,056	0,079	0,429	0,293	0,203	0,817	1,224
	NumberofPhotos	0,009	0,001	0,188	9,982	0,000	0,007	0,011	0,386	0,261	0,179	0,905	1,105
	DistanceTo	-0,050	0,007	-0,135	-7,435	0,000	-0,063	-0,037	-0,195	-0,197	-0,133	0,977	1,023
6	(Constant)	3,743	0,097		38,659	0,000	3,553	3,933					
	Private	-0,539	0,022	-0,486	-24,593	0,000	-0,582	-0,496	-0,606	-0,554	-0,437	0,809	1,237
	Shared	-1,016	0,064	-0,286	-15,900	0,000	-1,142	-0,891	-0,234	-0,396	-0,283	0,974	1,027
	MaxGuests	0,072	0,006	0,239	12,014	0,000	0,060	0,083	0,429	0,309	0,214	0,800	1,250
	NumberofPhotos	0,008	0,001	0,175	9,266	0,000	0,006	0,010	0,386	0,243	0,165	0,887	1,127
	DistanceTo	-0,048	0,007	-0,130	-7,195	0,000	-0,061	-0,035	-0,195	-0,191	-0,128	0,974	1,027
	OverallRating	0,100	0,020	0,091	5,025	0,000	0,061	0,139	0,131	0,135	0,089	0,958	1,043
7	(Constant)	3,747	0,096		38,972	0,000	3,558	3,935					
	Private	-0,534	0,022	-0,482	-24,508	0,000	-0,576	-0,491	-0,606	-0,553	-0,433	0,807	1,240
	Shared	-0,966	0,064	-0,272	-14,999	0,000	-1,093	-0,840	-0,234	-0,377	-0,265	0,945	1,058
	MaxGuests	0,048	0,008	0,160	6,080	0,000	0,033	0,064	0,429	0,163	0,107	0,450	2,224
	NumberofPhotos	0,008	0,001	0,170	9,085	0,000	0,006	0,010	0,386	0,239	0,160	0,885	1,130
	DistanceTo	-0,051	0,007	-0,139	-7,706	0,000	-0,064	-0,038	-0,195	-0,204	-0,136	0,962	1,040
	OverallRating	0,094	0,020	0,085	4,722	0,000	0,055	0,132	0,131	0,127	0,083	0,953	1,049
	NumberofBedrooms	0,077	0,017	0,115	4,517	0,000	0,044	0,111	0,409	0,121	0,080	0,485	2,064

TABLE 11 Included Variables Part 1 Multiple Regression Analysis

8	(Constant)	3,691	0,097		38,006	0,000	3,501	3,882					
	Private	-0,536	0,022	-0,484	-24,694	0,000	-0,578	-0,493	-0,606	-0,556	-0,434	0,806	1,241
	Shared	-0,967	0,064	-0,272	-15,066	0,000	-1,093	-0,841	-0,234	-0,378	-0,265	0,945	1,058
	MaxGuests	0,046	0,008	0,154	5,877	0,000	0,031	0,062	0,429	0,157	0,103	0,448	2,233
	NumberofPhotos	0,007	0,001	0,158	8,305	0,000	0,006	0,009	0,386	0,220	0,146	0,853	1,172
	DistanceTo	-0,051	0,007	-0,138	-7,668	0,000	-0,064	-0,038	-0,195	-0,204	-0,135	0,961	1,040
	OverallRating	0,093	0,020	0,085	4,736	0,000	0,055	0,132	0,131	0,127	0,083	0,953	1,049
	NumberofBedrooms	0,080	0,017	0,119	4,695	0,000	0,047	0,113	0,409	0,126	0,083	0,483	2,069
	ListedMonths	0,002	0,001	0,062	3,441	0,001	0,001	0,004	0,132	0,093	0,061	0,955	1,047
9	(Constant)	3,662	0,097		37,770	0,000	3,471	3,852					
	Private	-0,527	0,022	-0,476	-24,263	0,000	-0,570	-0,484	-0,606	-0,550	-0,424	0,797	1,255
	Shared	-0,968	0,064	-0,273	-15,162	0,000	-1,093	-0,843	-0,234	-0,380	-0,265	0,945	1,058
	MaxGuests	0,048	0,008	0,161	6,134	0,000	0,033	0,064	0,429	0,164	0,107	0,446	2,241
	NumberofPhotos	0,008	0,001	0,168	8,802	0,000	0,006	0,010	0,386	0,232	0,154	0,836	1,196
	DistanceTo	-0,051	0,007	-0,139	-7,778	0,000	-0,064	-0,038	-0,195	-0,206	-0,136	0,961	1,041
	OverallRating	0,097	0,020	0,089	4,951	0,000	0,059	0,136	0,131	0,133	0,087	0,951	1,052
	NumberofBedrooms	0,077	0,017	0,114	4,542	0,000	0,044	0,110	0,409	0,122	0,079	0,482	2,073
	ListedMonths	0,003	0,001	0,084	4,452	0,000	0,002	0,005	0,132	0,120	0,078	0,868	1,152
	NumberOfReviews	-0,001	0,000	-0,072	-3,827	0,000	-0,002	-0,001	-0,011	-0,103	-0,067	0,859	1,164
10	(Constant)	3,657	0,097		37,766	0,000	3,467	3,847					
	Private	-0,526	0,022	-0,474	-24,225	0,000	-0,568	-0,483	-0,606	-0,549	-0,423	0,796	1,256
	Shared	-0,961	0,064	-0,271	-15,063	0,000	-1,087	-0,836	-0,234	-0,378	-0,263	0,943	1,060
	MaxGuests	0,049	0,008	0,164	6,255	0,000	0,034	0,065	0,429	0,167	0,109	0,445	2,248
	NumberofPhotos	0,008	0,001	0,170	8,880	0,000	0,006	0,010	0,386	0,234	0,155	0,836	1,197
	DistanceTo	-0,051	0,007	-0,138	-7,753	0,000	-0,064	-0,038	-0,195	-0,206	-0,135	0,961	1,041
	OverallRating	0,095	0,020	0,087	4,833	0,000	0,056	0,134	0,131	0,130	0,084	0,948	1,055
	NumberofBedrooms	0,076	0,017	0,112	4,466	0,000	0,042	0,109	0,409	0,120	0,078	0,482	2,076
	ListedMonths	0,003	0,001	0,082	4,389	0,000	0,002	0,005	0,132	0,118	0,077	0,867	1,153
	NumberOfReviews	-0,001	0,000	-0,076	-3,996	0,000	-0,002	-0,001	-0,011	-0,108	-0,070	0,854	1,171
	Moderate	0,042	0,019	0,038	2,172	0,030	0,004	0,080	0,053	0,059	0,038	0,980	1,021
11	(Constant)	3,645	0,097		37,718	0,000	3,455	3,834					
	Private	-0,522	0,022	-0,471	-24,107	0,000	-0,565	-0,480	-0,606	-0,547	-0,420	0,794	1,260
	Shared	-0,947	0,064	-0,267	-14,833	0,000	-1,072	-0,821	-0,234	-0,373	-0,258	0,937	1,067
	MaxGuests	0,047	0,008	0,158	6,040	0,000	0,032	0,063	0,429	0,162	0,105	0,442	2,260
	NumberofPhotos	0,008	0,001	0,161	8,365	0,000	0,006	0,009	0,386	0,221	0,146	0,817	1,223
	DistanceTo	-0,051	0,007	-0,138	-7,789	0,000	-0,064	-0,038	-0,195	-0,207	-0,136	0,961	1,041
	OverallRating	0,095	0,020	0,087	4,855	0,000	0,057	0,134	0,131	0,131	0,085	0,948	1,055
	NumberofBedrooms	0,074	0,017	0,110	4,386	0,000	0,041	0,107	0,409	0,118	0,076	0,481	2,077
	ListedMonths	0,003	0,001	0,077	4,127	0,000	0,002	0,004	0,132	0,111	0,072	0,861	1,162
	NumberOfReviews	-0,001	0,000	-0,076	-4,014	0,000	-0,002	-0,001	-0,011	-0,108	-0,070	0,854	1,171
	Moderate	0,071	0,021	0,065	3,303	0,001	0,029	0,113	0,053	0,089	0,058	0,784	1,276
	Strict	0,072	0,024	0,061	3,030	0,002	0,025	0,119	0,188	0,082	0,053	0,743	1,347

a. Dependent Variable: LogADR

TABLE 12 Included Variables Part 2 Multiple Regression Analysis

STEPWISE EXCLUDED VARIABLES

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	Superhost	.064[b]	2,966	0,003	0,080	0,997	1,003	0,997
	Professional	.002[b]	0,112	0,911	0,003	0,956	1,046	0,956
	NumberofBedrooms	.253[b]	11,809	0,000	0,304	0,914	1,094	0,914
	DistanceTo	-.132[b]	-6,210	0,000	-0,166	0,989	1,011	0,989
	Shared	-.301[b]	-15,013	0,000	-0,376	0,989	1,011	0,989
	BusinessReady	-.017[b]	-0,806	0,420	-0,022	0,997	1,003	0,997
	MaxGuests	.230[b]	10,265	0,000	0,268	0,853	1,173	0,853
	Moderate	.052[b]	2,419	0,016	0,065	1,000	1,000	1,000
	Strict	.114[b]	5,335	0,000	0,143	0,985	1,015	0,985
	ListedMonths	.113[b]	5,299	0,000	0,142	0,999	1,001	0,999
	InstantbookEnabled	-.012[b]	-0,562	0,574	-0,015	0,999	1,001	0,999
	NumberOfBookingsLTM	.016[b]	0,725	0,469	0,020	0,995	1,005	0,995
	NumberOfReviews	.019[b]	0,884	0,377	0,024	0,998	1,002	0,998
	OverallRating	.103[b]	4,811	0,000	0,129	0,998	1,002	0,998
	NumberofPhotos	.260[b]	12,392	0,000	0,318	0,946	1,057	0,946
2	Superhost	.051[c]	2,581	0,010	0,070	0,996	1,004	0,987
	Professional	.016[c]	0,765	0,444	0,021	0,954	1,048	0,944
	NumberofBedrooms	.224[c]	11,178	0,000	0,289	0,905	1,105	0,899
	DistanceTo	-.122[c]	-6,186	0,000	-0,165	0,988	1,013	0,977
	BusinessReady	-.014[c]	-0,723	0,470	-0,020	0,997	1,003	0,986
	MaxGuests	.246[c]	11,978	0,000	0,308	0,851	1,175	0,847
	Moderate	.035[c]	1,761	0,078	0,048	0,997	1,003	0,986
	Strict	.097[c]	4,885	0,000	0,131	0,981	1,019	0,973
	ListedMonths	.110[c]	5,597	0,000	0,150	0,999	1,001	0,988
	InstantbookEnabled	-.022[c]	-1,118	0,264	-0,030	0,998	1,002	0,988
	NumberOfBookingsLTM	.022[c]	1,095	0,274	0,030	0,994	1,006	0,984
	NumberOfReviews	.015[c]	0,736	0,462	0,020	0,997	1,003	0,987
	OverallRating	.094[c]	4,731	0,000	0,127	0,997	1,003	0,987
	NumberofPhotos	.230[c]	11,740	0,000	0,303	0,936	1,068	0,932
3	Superhost	.055[d]	2,891	0,004	0,078	0,995	1,005	0,846
	Professional	-.023[d]	-1,170	0,242	-0,032	0,929	1,077	0,791
	NumberofBedrooms	.116[d]	4,328	0,000	0,116	0,494	2,023	0,465
	DistanceTo	-.144[d]	-7,677	0,000	-0,203	0,980	1,021	0,832
	BusinessReady	-.008[d]	-0,434	0,665	-0,012	0,996	1,004	0,844
	Moderate	.046[d]	2,442	0,015	0,066	0,994	1,006	0,847
	Strict	.062[d]	3,193	0,001	0,086	0,955	1,047	0,828
	ListedMonths	.094[d]	4,997	0,000	0,134	0,994	1,007	0,846
	InstantbookEnabled	-.025[d]	-1,316	0,188	-0,036	0,998	1,002	0,847
	NumberOfBookingsLTM	-.009[d]	-0,487	0,626	-0,013	0,976	1,025	0,835
	NumberOfReviews	-.004[d]	-0,190	0,849	-0,005	0,991	1,009	0,843
	OverallRating	.124[d]	6,562	0,000	0,175	0,982	1,019	0,838
	NumberofPhotos	.195[d]	10,171	0,000	0,265	0,907	1,102	0,824
4	Superhost	.031[e]	1,676	0,094	0,045	0,979	1,022	0,822
	Professional	-.033[e]	-1,762	0,078	-0,048	0,926	1,080	0,768
	NumberofBedrooms	.101[e]	3,910	0,000	0,105	0,493	2,029	0,461
	DistanceTo	-.135[e]	-7,435	0,000	-0,197	0,977	1,023	0,812
	BusinessReady	-.016[e]	-0,898	0,369	-0,024	0,994	1,006	0,822
	Moderate	.046[e]	2,523	0,012	0,068	0,994	1,006	0,823
	Strict	.033[e]	1,768	0,077	0,048	0,933	1,072	0,809
	ListedMonths	.061[e]	3,276	0,001	0,088	0,958	1,044	0,823
	InstantbookEnabled	-.025[e]	-1,385	0,166	-0,037	0,998	1,002	0,824
	NumberOfBookingsLTM	-.047[e]	-2,504	0,012	-0,068	0,940	1,064	0,806
	NumberOfReviews	-.043[e]	-2,271	0,023	-0,061	0,952	1,051	0,815
	OverallRating	.099[e]	5,354	0,000	0,143	0,962	1,040	0,807

TABLE 13 Excluded Variables Part 1 Multiple Regression Analysis

5	Superhost	.027[f]	1,488	0,137	0,040	0,978	1,023	0,809
	Professional	-.032[f]	-1,702	0,089	-0,046	0,926	1,080	0,757
	NumberofBedrooms	.123[f]	4,833	0,000	0,130	0,487	2,053	0,461
	BusinessReady	-.019[f]	-1,069	0,285	-0,029	0,994	1,006	0,810
	Moderate	.044[f]	2,433	0,015	0,066	0,994	1,006	0,811
	Strict	.035[f]	1,901	0,057	0,051	0,933	1,072	0,802
	ListedMonths	.058[f]	3,156	0,002	0,085	0,957	1,045	0,811
	InstantbookEnabled	-.025[f]	-1,386	0,166	-0,038	0,998	1,002	0,811
	NumberOfBookingsLTM	-.051[f]	-2,759	0,006	-0,075	0,940	1,064	0,793
	NumberOfReviews	-.047[f]	-2,566	0,010	-0,069	0,951	1,052	0,802
	OverallRating	.091[f]	5,025	0,000	0,135	0,958	1,043	0,800
6	Superhost	.014[g]	0,790	0,430	0,021	0,958	1,044	0,800
	Professional	-.022[g]	-1,209	0,227	-0,033	0,916	1,091	0,756
	NumberofBedrooms	.115[g]	4,517	0,000	0,121	0,485	2,064	0,450
	BusinessReady	-.017[g]	-0,959	0,338	-0,026	0,993	1,007	0,799
	Moderate	.038[g]	2,151	0,032	0,058	0,990	1,010	0,799
	Strict	.038[g]	2,060	0,040	0,056	0,932	1,073	0,787
	ListedMonths	.058[g]	3,195	0,001	0,086	0,957	1,045	0,799
	InstantbookEnabled	-.019[g]	-1,045	0,296	-0,028	0,993	1,007	0,800
	NumberOfBookingsLTM	-.058[g]	-3,153	0,002	-0,085	0,935	1,070	0,789
	NumberOfReviews	-.051[g]	-2,823	0,005	-0,076	0,949	1,054	0,798
7	Superhost	.014[h]	0,797	0,426	0,022	0,958	1,044	0,450
	Professional	-.014[h]	-0,734	0,463	-0,020	0,906	1,104	0,436
	BusinessReady	-.014[h]	-0,803	0,422	-0,022	0,992	1,008	0,450
	Moderate	.036[h]	2,031	0,042	0,055	0,989	1,011	0,449
	Strict	.037[h]	2,031	0,042	0,055	0,932	1,073	0,446
	ListedMonths	.062[h]	3,441	0,001	0,093	0,955	1,047	0,448
	InstantbookEnabled	-.015[h]	-0,852	0,394	-0,023	0,991	1,009	0,449
	NumberOfBookingsLTM	-.053[h]	-2,878	0,004	-0,078	0,931	1,075	0,442
	NumberOfReviews	-.047[h]	-2,587	0,010	-0,070	0,945	1,058	0,447
8	Superhost	.009[i]	0,471	0,638	0,013	0,949	1,054	0,448
	Professional	-.020[i]	-1,093	0,274	-0,030	0,896	1,116	0,435
	BusinessReady	-.013[i]	-0,725	0,469	-0,020	0,991	1,009	0,448
	Moderate	.033[i]	1,842	0,066	0,050	0,986	1,014	0,447
	Strict	.034[i]	1,852	0,064	0,050	0,929	1,076	0,444
	InstantbookEnabled	-.008[i]	-0,471	0,638	-0,013	0,979	1,022	0,447
	NumberOfBookingsLTM	-.056[i]	-3,097	0,002	-0,084	0,927	1,078	0,441
	NumberOfReviews	-.072[i]	-3,827	0,000	-0,103	0,859	1,164	0,446
9	Superhost	.025[j]	1,382	0,167	0,037	0,900	1,112	0,446
	Professional	-.022[j]	-1,198	0,231	-0,032	0,896	1,117	0,434
	BusinessReady	-.010[j]	-0,569	0,569	-0,015	0,990	1,010	0,446
	Moderate	.038[j]	2,172	0,030	0,059	0,980	1,021	0,445
	Strict	.031[j]	1,729	0,084	0,047	0,928	1,077	0,443
	InstantbookEnabled	.008[j]	0,418	0,676	0,011	0,927	1,079	0,446
	NumberOfBookingsLTM	-.012[j]	-0,442	0,659	-0,012	0,430	2,325	0,399
10	Superhost	.025[k]	1,377	0,169	0,037	0,900	1,112	0,444
	Professional	-.020[k]	-1,055	0,292	-0,029	0,891	1,122	0,433
	BusinessReady	-.011[k]	-0,622	0,534	-0,017	0,989	1,011	0,445
	Strict	.061[k]	3,030	0,002	0,082	0,743	1,347	0,442
	InstantbookEnabled	.009[k]	0,492	0,623	0,013	0,926	1,080	0,445
	NumberOfBookingsLTM	-.019[k]	-0,700	0,484	-0,019	0,424	2,357	0,398
11	Superhost	.023[l]	1,253	0,210	0,034	0,898	1,114	0,442
	Professional	-.021[l]	-1,132	0,258	-0,031	0,891	1,122	0,431
	BusinessReady	-.014[l]	-0,782	0,434	-0,021	0,986	1,014	0,442
	InstantbookEnabled	.010[l]	0,577	0,564	0,016	0,925	1,081	0,442
	NumberOfBookingsLTM	-.019[l]	-0,708	0,479	-0,019	0,424	2,357	0,398

a. Dependent Variable: LogADR

b. Predictors in the Model: (Constant), Private

c. Predictors in the Model: (Constant), Private, Shared

d. Predictors in the Model: (Constant), Private, Shared, MaxGuests

e. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos

f. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo

g. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating

h. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms

i. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths

j. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews

k. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews, Moderate

l. Predictors in the Model: (Constant), Private, Shared, MaxGuests, NumberofPhotos, DistanceTo, OverallRating, NumberofBedrooms, ListedMonths, NumberOfReviews, Moderate, Strict

TABLE 14 Excluded Variables Part 2 Multiple Regression Analysis