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FACULTY OF ENGINEERING
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Literature Review Report

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CENG 407

Innovative System Design and Development I

202002
AIRBNB PRICE DETERMINANTS

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Table of Contents

Abstract

Airbnb is a platform to share houses for a short stay with those who prefer houses to hotels. Airbnb is also known as sharing economy accommodation service and peer to peer accommodation. The platform puts the responsibility of determining the price of the hosts. Due to Airbnb's unique nature, hosting pricing strategies are very different from the traditional hospitality industry. The prices are not determined randomly. In fact, many features such as location, availability of public transportation, size of the rented house, the existence of shopping places in the neighborhood, and so on, affect the price. In this project, the data from the official site of Airbnb will be used to determine which attributes are the most decisive ones in determining the price. The developed model can be used by hosts and owners of properties to estimate the prices more accurately. Thus, in addition to accurate pricing, it can offer advantages such as a more systematic, easy and helpful approach.

Airbnb, evi otele tercih edenlerle kısa süreli konaklama için evleri paylaşabileceğiniz bir platformdur. Airbnb, aynı zamanda ekonomi konaklama hizmetinin paylaşılması ve eşler arası konaklama olarak da bilinir. Platform, ev sahiplerinin fiyatını belirleme sorumluluğunu üstlenir. Airbnb'nin benzersiz doğası nedeniyle, ev sahipliği fiyatlandırma stratejileri geleneksel konaklama endüstrisinden çok farklıdır. Fiyatlar rastgele belirlenmez. Nitekim lokasyon, toplu taşıma araçlarının kullanılabilirliği, kiralanan evin büyüklüğü, mahallede alışveriş yerlerinin varlığı gibi pek çok özellik fiyatı etkilemektedir. Bu projede Airbnb' nin resmi sitesinden alınan veriler, fiyatın belirlenmesinde hangi özelliklerin en belirleyici olduğunu belirlemek için kullanılacaktır. Geliştirilen model, fiyatları daha doğru tahmin etmek için ev sahipleri ve mülk sahipleri tarafından kullanılabilir. Böylelikle doğru fiyatlandırmanın yanı sıra daha sistematik, kolay ve yardımcı bir yaklaşım gibi avantajlar da sunabilir.

1. Introduction

Airbnb is a web application that enables people to find a place to stay on their travels and rent by owners. Airbnb, offering over 800 thousand rental options in 33 thousand cities in 192 countries; It was established in San Francisco, USA in August 2008. Airbnb is also referred to as sharing economy and peer to peer accommodation in the literature.

In the field of sharing economy, Airbnb acts as a new and alternative business model in the hospitality industry.As mentioned earlier, Airbnb, founded in 2008, has become a leading peer-to-peer accommodation platform with more than 5 million listings in 81,000 cities around the world [1]. The essence and rapid success of Airbnb lies in the effective mix of various key factors such as affordable prices and economic benefits, originality and unique consumer experience, sustainability, perceived attractiveness and responsiveness. Beyond all these advantages, price and low cost are frequently reported as one of the most important factors facilitating the rapid spread of the peer to peer accommodation sharing phenomenon.

It differs from other types of accommodation due to its unique structure and the different features mentioned. One of these differences is the pricing strategy. Since Airbnb is different from traditional accommodation, many features should be considered in price determination. Each feature should be passed through different evaluation scales, and then its positive and negative impact on the price should be evaluated. Therefore, pricing should be done in detail.

2. Literature Review

2.1. Airbnb and Sharing Economy

As mentioned before, due to the structure of airbnb, it is also referred to as sharing economy. First of all, sharing as a human activity has been in our lives since ancient times. However, the "cooperative consumption" and "sharing economy" have spread considerably with the advancement of internet technology. In the times of sharing the economy or the peer economy, individuals rent, lend or trade goods, services, transport or space in a peer-to-peer manner. Including all the activities mentioned above, tourism is one of the areas most affected by the sharing economy. In recent years, shared economy-based business models have been developed in transportation such as Uber.com and hospitality such as Airbnb.com due to high tourist demand. [1]

Certainly, for these reasons, the sustainability of these demands is an important issue. With regard to sustainability, the sharing economy emerging in the tourism industry has a higher probability than the traditional industry. Through the use of under-utilized assets, the sharing economy can increase the quantity of services without additional construction or acquisition, which can reduce the industry's environmental footprint. Several studies have shown that consumers of the sharing economy pay more attention to the local community and the environment, thus leading to reduced energy and water consumption of both consumers and suppliers and reduced waste generation. Due to these factors, its place in our lives, its sustainability, is higher than other tourism industries.

Moreover, the sharing economy increases the local community's employment rate as well as the community's profit. For example, Airbnb's message of "travelers coming to your neighborhood" to tourists encourages them to have new experiences by sharing the same space with members of the local community, which makes Airbnb tourists more involved in economic activities in local areas, such as eating at a local restaurant. This also benefits the development of the economy.Providing idle assets to the sharing economy, the community's human capital acts as a bridge between these opportunities and helps consumers to respect community culture and resolve social imbalances. [3]

2.2. Differences in Hospitality Industry

As a leading platform for peer-to-peer hospitality products, Airbnb is a "creative destruction " for the traditional hospitality industry. Unlike hotels, the host-guest relationship on Airbnb is quite different from the staff-customer relationship. Both Airbnb hosts and guests seek more than functional value. Experiential value, originality, sociability and trust are very important for Airbnb users. Also, Airbnb affects the performance of hotels. Airbnb is found to have a substitution effect on hotels because Airbnb procurement adversely affects the financial performance of hotels.

Moreover, the sharing economy has its own characteristics compared to hotels, mainly due to accommodation and housing based service. These unique features make it difficult to apply the hospitality industry's traditional understanding to the recognition of the value of users, such as star rating, which is the most well-known and widely used system in the hospitality industry. However, the star rating system based on user reviews has a limited effect on the price of Airbnb listings, unlike the hotel industry. Indirect signals such as service duration and personal information of the hosts at Airbnb are considered alternative sources of trust and their impact on price is significant. [3]

In other words, it is generally accepted that the most critical features for hotel pricing are star ratings and location. This rating can be perceived as an index signal evaluated by an independent organization that does not benefit from biased reporting of hotel quality and experience. Therefore, the star rating system is also extremely effective for customers and hotels. Some studies have also shown that star ratings of hotels have high explanatory power over hotel prices. Experimental studies have revealed that the sea view, the city center and the transportation center are the most considered location factors in hotel pricing. However, this situation differs for accommodation types such as Airbnb as mentioned above.

2.3. Price Determinants Of Airbnb

First of all, as mentioned in the previous sections, price determination involves quite different approaches due to the unique characteristics of Airbnb.

The difference between Airbnb listings and hotels is not just as much as those mentioned in the previous section ,not only because of the real estate, but also because of the service, the amenities, the hosts' personality, and the local communities.Therefore, the accumulated revenue management knowledge in the hospitality industry cannot be directly applied to the sharing economy accommodations. Most pricing studies on Airbnb have shown that the main difference between Airbnb and hotels is the standardization of jobs. When it comes to hotels, the form and format of services are quite similar across hotels due to standardization. Thus, consumers can easily recognize or compare the values of the service with these industrial service standards. Unlike hotels, every listing on Airbnb has unique features that are difficult to compare. However, Airbnb's user interface provides customers with standard registration information. In this way, customers understand the value of listings through the platform's user interface. [3]

According to this interface on Airbnb, this is as follows: although customer reviews are ,actually like the logic in this star rating, still meaningful indicators of price, customers have started looking for other signals to eliminate bias. Experimental studies have found that host status, the service length of the listing, and the superhost badge etc. are now more often used by customers to gauge the quality and value of a listing. The characteristics of the given property and the number, size and type of rooms also showed statistically significant effects on the price of Airbnb listings through product differentiation such as hotels.

If the above-mentioned Airbnb's pricing features are to be opened in more detail, the table below, figure 1, will help. In addition, the effect of these features ,such as positive or negative, on the price is also specified.

Category	Determinants	Effects
Listing attributes	• Room type[a] (reference group: shared room), number of bedrooms[a], number of bathrooms[a], number of accommodations[a], free parking[b], pool, gym, real bed, wireless Internet, number of accommodation photos	positive
	• Accommodation type (reference group: independent properties), free breakfast[b]	negative
	• Months since the listing was established	insignificant
Host attributes	• Hosts' listing count, host verification, host profile picture, response time	positive
	• Race (reference group: white)	negative
	• Gender, marital status, sexual orientation, acceptance rate	insignificant
	• Superhost or not[a], professional (multilisting) or not	mixed
Listing reputation	• Rating on cleanliness, rating on location	positive
	• Number of reviews[a], rating on value	negative
	• Rating on accuracy, rating on check in	insignificant
	• Overall rating score[a], rating on communication	mixed
Rental policies	• Strict cancellation policy[b], guests' phone verification required	positive
	• Instant bookable[b], smoking allowed	negative
	• Guests' profile photo required	insignificant
Listing location	• Neighborhood value, average rental price in the district, number of Airbnb listings in the same district, price of surrounding Airbnb listings and hotels, number of points of interest (POIs) in surrounding area, located within sightseeing, eating or shopping areas, located near a continuous coastal fringe	positive
	• Distance to city center, number of hotels in the same district	negative
	• Distance to the nearest highway	insignificant

Figure 1: Price Determinants of Airbnb Listings

Listing Attributes:The first category of Airbnb price determinants are listing attributes. Accommodation type and room type determine Airbnb room prices. The number of bedrooms, bathrooms, and number of accommodations also have a positive effect on the Airbnb rental price. Social facilities such as parking, swimming pool and wireless internet positively affect the Airbnb listing price. Conversely, recent research on hotels found that free parking does not have a significant effect on the hotel room price. This is because free parking has already become a standard service in hotels in recent years. In the peer-to-peer rental industry, parking can be part of the homeowners' personal property, so they differ. Inclusion of breakfast has a negative effect on Airbnb room price, which does not match the findings in hotel studies. Also, the number of accommodation photos positively affect the Airbnb price and the number of reviews. [1]

Host Attributes Another important price determinant of Airbnb is host features. Hosts, for example, found that Asian and Hispanic hosts get a lower price on Airbnb compared to their white counterparts. Current researches have not found a significant impact of the host's gender, marital status, or sexual orientation on Airbnb room rate. However, verifying the host's profile or providing the host's photo on Airbnb can result in a price premium because this type of action increases the host's trustworthiness. In particular, a "superhost" badge on Airbnb helps to gain as much difference as the additional room rate. According to several studies, "Professional hosts" , professional means the host has two or more listings on Airbnb, can win a daily revenue of each property than their non-professional counterparts. However, professional landlords have a higher daily income for each property as the occupancy rate is higher. The more Airbnb listings owned by a host, the higher the room rate is charged. Although hosts' acceptance rate does not have a significant effect on the price, longer response time is associated with a higher room rate. [1]

Listing Reputation: The main point in this category is reputation. The number of reviews negatively affects the list price, but also positively affects the daily revenue and occupancy rate of each property. The quantity of reviews represents the size of the demand and there is more demand for cheaper listings. As mentioned earlier, customer evaluation has a mixed effect on the room rate. There are studies supporting both positive and negative effects of the overall rating score. On the other hand, the accuracy and rating score on check-in do not affect the price. A higher score on cleanliness, communication efficiency and location wins a price premium. However, rating score on value has a negative effect on Airbnb listing price. [1]

Rental Policies: Another category is related to rental policies. For example, instantly bookable lists are less expensive. Refundable cancellation policy is associated with lower rental prices, which contradicts findings from hotel researches. Also, allowing smoking negatively affects the Airbnb room rate. While requiring guests for phone verification is also associated with a higher room rate, requiring profile photo of guests does not affect the Airbnb listing price. [1]

Listing Location: The last category is listing location. Like hotels, locational factors are taken into account in Airbnb's pricing strategy . The closeness to the city center and the coastline results in higher room rates. If a place is located in an seeing the surroundings, eating or shopping area, it also wins a price premium. The number of points of interest in the surrounding areas is positively correlated with Airbnb listing price. Neighborhood value shows a positive but declining rate of return on Airbnb list price. However, a shorter distance to the highway does not have a significant effect on the Airbnb rental price because in this case the distance to the city center is more important. While the number of Airbnb listings in the same region increases the rental price, market competition is also important as the hotel density negatively affects the Airbnb listing price. Higher rents in the region and the room rate of Airbnb listings in the surrounding area also increase the Airbnb price. [1]

2.4. Pricing Methods

Academic research on the pricing of the sharing economy is still continues. Generally, there are two pricing models for sharing economy platforms. The first model is entirely algorithm-based, which means the firm has full control over the prices of each service request. The second pricing model uses algorithm tools for reference only and leaves the pricing decision open to service providers. Sharing econmy based accommodation products such as Airbnb fall into the second category.

Model in 2020:

The most emphasized situations in this year's studies are as follows: current Airbnb pricing studies did not take into account spatial differences and important geographic information enough to estimate the effect of pricing variables. The effect of pricing variables may have local variations that indicate different dynamics between factors in the field.

To better reflect this spatial difference, geographically weighted regression (GWR) has been used for pricing research for hotels and Airbnb hosts, and stays in the sharing economy. However, there is a problem here. The reason is that the GWR does not take into account a changing spatial heterogeneity scale and thinks that all variables have the same operating scale. Pricing variables are spatial processes that determine the price, and each must operate at a different scale from local to global. However, to date, there has been no research study considering this multi-scale regression approach for Airbnb pricing analysis.[3]

The second problem is that the distance to tourism destinations, which is an important decision criterion for accommodation, is neglected. Tourists are Airbnb's most frequent customers, so the distance criteria must be included in Airbnb pricing research. Several previous studies have considered the distance variable in pricing models. However, they have used similar points such as the city center and highway exits for tourism destinations, but this is not the right approach. A tourist will evaluate the accessibility to multiple tourism destinations to make their accommodation decisions. Therefore, the distance to more than one tourism destination should be considered in Airbnb pricing research. [3]

If the GWR model is examined in more detail: GWR captures the spatial difference in pricing strategies by performing a localized estimate of the effect of pricing variables. The basic idea of the GWR is to directly capture the geographic variance in regression estimates across space. Calculates the localized regression coefficients of the given explanatory variables for a given location using only neighboring locations to show the changing effect of pricing variables. Neighborhood is defined by search bandwidth, which is a reflection of the concept of scale of operations.

However, the scale of operation must vary due to its nature. It may differ for each pricing variable. For example, management variables such as cancellation policy and superhost status are likely to show a similar trend at the regional or global level. Other variables such as the number of bedrooms, the number of guests and the distance to tourism destinations will have a more local scale of the operation as their impact will be more sensitive to the local environment.

A limiting feature of the GWR is that it implements the same operation scale for all explanatory variables, ignoring the possibility of variable scale. Assuming that all pricing variables have the same scale of operation, this would result in false spatial variances in global variables. In this case, the differences in operation scale between local variables will also be ignored. [3]

Because of these stated constraints, a different regression model should be used to accurately analyze the impact of pricing variables on Airbnb price and show the use of different operational scales:

Multiscale Geographically Weighted Regression: It is a regression model that predicts the relationships between explanatory and response variables. Conventional models such as OLS assume the same relationships globally in a given region, the case of using the same scale. Therefore, they predict relationships using all cases of the same weight level, expressed as correlation coefficients. If we apply this logic to the Airbnb pricing strategy, we assume that all hosts in the region independently use the same logic and criteria to determine their prices. However, this is not the correct approach. [3]

To avoid these problems mentioned above, Fotheringham et al. (2017) proposed another GWR variation, the multiscale GWR (MGWR). The basic idea of MGWR is to use different search bandwidth, scale of operations to estimate its coefficient for each explanatory variable. Bandwidths are determined by data rather than by external factors.

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(\mu_i, v_i)x_{ij} + \epsilon_i, i = 1, \dots, n$$

Figure 2: MGWR Function

Here, the jth shows the scale of operation (bandwidth) of the explanatory variable. To determine the bandwidth, MGWR uses a different approach than the GWR in that it must derive more than one different bandwidth for given variables simultaneously, the back-fitting approach. This back fitting starts from the ordinary GWR estimation and tests the goodness of fit for each variable to find the optimal bandwidth to reflect the operation scale specified in the given dataset. [3]

Thus, the MGWR results reveal that the scale of operations varies greatly between variables, and indicates that even for the identical variable, the scale of operations will differ even between cities. Based on bandwidth and statistical distribution of coefficients in each city, it classifies pricing variables as local, regional, and global variables.

Additionally, global variables can be interpreted in two ways: (1) Airbnb hosts in each city use similar pricing strategies regarding these variables, and/or (2) the hosts are influenced by other competitors' pricing strategy related to these variables' city-wide scale .[3]

Model in 2019:

Studies in 2019 are based on Hedonic regression models. These studies focus on the algorithm perspective of pricing. Based on previous research on Airbnb pricing, the authors identify five sets of explanatory variables in Figure 1: listing attributes, host features, ranking reputation, leasing policies, listing position.

Semi-logarithm hedonic price models are used to estimate the effects of explanatory variables on price. The hedonic price model was developed by Rosen (1974) to measure the marginal effects of a product's properties on price. The original function was written as :

$$P = F\,(Z, \varepsilon) \qquad (1)$$

Figure 3: The Original Hedonic Price Function

where P is the observed price of a product, Z is a vector of the product's features or utilities, and ε is the standard error [1].

Here, the semilog form of the hedonic price function is used and stated as:

$$\ln P = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \qquad (2)$$

Figure 4: Semilog Form of Hedonic Price Function

lnP is the log form of the observed price of a sample list, β_0 is the constant term, Xi is the ith explanatory variable, βt is the semi-precision of P with respect to Xi and ε is the error term [1].

In semi-logarithm functions, the exact percentage change in y caused by a change in x_i (controlling all other factors) is predicted as :

$$\Delta\hat{y} = \left(e^{\hat{\beta}_i \Delta x_i} - 1\right) \times 100\% \qquad (3)$$

Figure 5: Exact Percentage Change in y

Model in 2018:

The basic idea examined in 2018's study is that the determinants of Airbnb prices are strongly correlated with the location of the listings; for example, the closer it is to the city center, the more expensive the accommodation.

This year, a multivariate analysis technique is adopted that consists of estimating a hedonic price model, which is often used in market research of heterogeneous goods. This method is used to determine and quantify the relationship between Airbnb accommodation features and price. To estimate how these properties affect the price, the model is estimated using ordinary least squares (OLS), which adopts the known sequential steps method to select variables.

Considering the limitations mentioned above, the quantitative regression method (QRM) has been adopted. The advantage of this over the OLS prediction is that the significance of dependent variable determinants can be explained at any point in the distribution. Thus, the model is less affected since it is not necessary to construct an aleatory perturbation hypothesis. Therefore, the results from the estimation of both models ,OLS and QRM, allow the shadow price component of the list price generated by the accommodation features to be determined. [5]

For such models, prediction usually requires the logarithmic transformation of the dependent variable, which is the listing price. The literature highlights several reasons why semilogarrhythmic models are used frequently. For example, goodness of fit criteria applied to data to avoid heteroskedasticity and facilitate interpretation of coefficients. Due to the logarithmic transformation, the fit criteria show how the dependent variable presents percentage variables when the price has unitary changes in the independent variable. In addition, Sirmans et al. shows that hedonic models are estimated in logarithmic forms, most likely, that the implicit prices obtained for each property are not the same for all price ranges. [5]

The proposed OLS model is the following:

$$ln(P_i) = \alpha + \sum_{j=1}^{n} \beta_j X_{ij} + \sum_{k=1}^{m} \gamma_k D_{ik} + \varepsilon_i \quad (1)$$

where:

$ln\ (Pi)$ is the neperian logarithm of *daily_price* for the property "i"
α is the fixed component, which is independent from the market.
β_j is the parameter to be estimated, related to the characteristic "j".
X_{ij} is the continuous variable that considers the characteristic "j" of observation "i".
γ_k is the parameter to be estimated, related to the characteristic "k".
D_{ik} is the fictitious variable that considers the characteristic "k" of observation "i".
ε_i is the term of the error associated with the observation "i".

Figure 6: OLS model

Given the characteristics of the model, the effect of a change from 0 to 1 in a dummy variable on the price can be calculated using the expression (2) while keeping all other independent variables constant.[5]

$$\hat{p} = 100\left[exp\left(\hat{c} - \frac{1}{2}\hat{V}(\hat{c})\right) - 1\right] \quad (2)$$

Figure 7: Parameter

The quantitative regression method does not require certain criteria, as in the OLS model. Therefore, QRM allows to control nonlinearity. It may not be normal due to asymmetries, outliers and heteroskedasticity. OLS models rely on the conditional mean of the dependent variable when given certain values of the predictor variables, but do not provide information for other conditional quantities of the dependent variable. QRM allows modeling different conditional quantiles of the dependent variable, overcoming the limitations of OLS models.Therefore, it is possible to estimate the implicit value of each accommodation property for different price ranges or quantities as they may vary. Then, the effect of each feature can be predicted depending on the selling price ranges. That is, a QRM can be defined using a multiple linear regression model.

$$Y_i = X_i\beta_\theta + u_{\theta i} \tag{3}$$

where

Y_i is the dependent variable
X_i is the matrix of independent variables
β_θ is the vector of parameters to be estimated for quantile θ
$u_{\theta i}$ is the aleatory perturbation that corresponds to quantile θ.

Figure 8: QRM model

In this regression model, quantiles θ are defined for the dependent variable Yi, given the dependent variables Xi with Quant (Yi | Xi) = Xiβθ. Each quantile regression θ with 0 < θ <1 is defined as the solution to the minimization problem solved by the simplex linear programming model.

$$\min_{\beta \in R^k} \left\{ \sum_{i \in \{i: Y_i \geq X_i\beta\}} \theta |Y_i - X_i\beta_\theta| + \sum_{i \in \{i: Y_i < X_i\beta\}} (1-\theta)|Y_i - X_i\beta_\theta| \right\} \tag{4}$$

Figure 9 : Minimization Problem

Parameter estimation for QRM is formulated by minimizing the mean absolute deviation with asymmetric weights. In OLS, the square is obtained by minimizing the sum of residuals. Median regression is a special case for quantile regression where = 0.5, which is the only case where weights are symmetrical.

Quantile regression has been estimated using the statistical package R "quantreg", version 5.36. The goodness of fit of quantile models has been calculated from absolute deviations using the pseudo-R1. It is useful to compare quantile models, but since they are based on the variance of square deviations, they cannot be compared with the coefficient of determination obtained through OLS. The pseudo-R1 is obtained as the ratio between 1 minus the sum of absolute deviations in fully parameterized models and zero, ie the sum of absolute deviations in the non-conditional quantile model. [5]

Model in 2017:

The purpose of the study of 2017 is to determine the price determinants of sharing economy-based accommodation offers in the digital market, especially Airbnb.com. 180,533 accommodation rental offers from 33 cities listed on Airbnb.com are analyzed. Ordinary least squares (OLS) analysis and quantitative regression (QR) analysis are used to investigate price determinants in five categories: host features, site and property features, amenities and services, rental rules, and online review ratings. The findings have important implications for the design of pricing-recommendation systems for sharing economy-based accommodation service providers, such as the price recommendation tool recently launched by Airbnb.

Linear QR models and linear OLS regression models are used to determine linear relationships between a dependent variable and a set of explanatory variables. The main difference between types of models is: OLS regression models are based on the conditional mean of the dependent variable. However, QR models are based on the conditional τth quantile of the dependent variable, where τ (0, 1). QR therefore goes beyond the analysis of the conditional mean of a dependent variable, providing a more comprehensive description of the conditional distribution. In other words, QR measures the effects of individual explanatory variables on the entire distribution of the dependent variable, rather than predicting the average response of the dependent variable to changes in explanatory variables. This allows the analyst to reveal hidden price-response patterns that exist depending on the level of prices. [4]

QR is denoted as: assuming a random variable Y with probability distribution function $F(y) = \text{Prob}(Y \leq y)$, the τth quantile of Y can be defined as the smallest value of y satisfying $F(y) \geq \tau$: $Q(\tau) = \inf\{y: F(y) \geq \tau\}$, where $0 < \tau < 1$. For n observation of Y, the empirical distribution function is given as $F_n(y) = \sum 1 (Y_i \leq y)$, where 1 ,z, is an indicator function that takes the value 1 if the z argument is true, and 0 otherwise. Accordingly, quantities are defined as follows:[4]

$$Q_n(\tau) = \inf\{y: F(y) \geq \tau\}.$$

Figure 10: Quantitative Regression

This expression is given as an optimization problem below:

$$Q_n(\tau) = \arg\min_{\xi} \left\{ \sum_{i:Y_i \geq \xi} \tau |Y_i - \xi| + \sum_{i:Y_i < \xi} (1-\tau) |Y_i - \xi| \right\} = \arg\min_{\xi} \left\{ \sum_i \rho_\tau |Y_i - \xi| \right\},$$

Figure 11: Quantitative Regression With Optimization Problem

The rt(u) = u(τ -1(u < 0)) is the so-called check function, which weights positive and negative values asymmetrically. A linear specification of the conditional quantile of the dependent variable gives Q(τ|Xi,β(τ)) = Xi'β(τ), where Xi is the vector of the explanatory variables and β(τ) is the vector of the coefficients associated with the tth quantile. Considering these conditions, the previous optimization problem is as follows: [4]

$$\hat{\beta}_n(\tau) = \arg\min_{\beta(\tau)} \left\{ \sum_i \rho_\tau (Y_i - X_i' \beta(\tau)) \right\}.$$

Figure 12: Optimization Problem

QR parameters are estimated taking into account the different weights of the absolute residues. To analyze the listing prices, the price per person per night variable is chosen as the dependent variable, in logarithmically. Since the resulting expression is a semi-logarithmic specification, the coefficient values represent the semi elasticities, that is, the percentage change in price when an explanatory variable changes varies by 1. Bearing in mind that the effect of the dummy independent variable on the log dependent variable is: measured by eβ -1.

As a result of this study, the OLS analysis reveals that 24 of the 25 variables examined are good predictors for the price, while the QR analysis shows that all variables have significant effects on the price and these effects are generally dependent on the price range. Thus, the findings provide insights into the complexity of the price-determining relationship in sharing economy-based accommodation rents.

3. Aim of The Project

As can be seen in these literature studies, the issue of Airbnb price determination is a very detailed and extensive subject. There are many different price determining variables. There are many methods with different features, advantages, limitations etc. With this project, the most effective attributes in price determination will be determined. A model will be developed for a more effective and more accurate pricing. This model will be accessible by host and owners. Thus, they will be provided with the necessary informations to provide a more helpful, effective and accurate pricing option.

4. Conclusion

As a result of this study, we examined similar studies conducted in 2017, 2018, 2019 and 2020 for our Airbnb price determinant project. In addition, we tried to explain why, when and for what Airbnb is used for those who do not know about Airbnb, which is a sharing economy business model. Besides, we examined the researches in the literature, models and some results obtained. While some of the results obtained about price determinants are still unclear, others open to discussion. One of the main reasons of these is that many factors affect price determinants in rapidly developing cities. Naturally, this situation creates difficulties for researchers in collecting data. Even some cases that affect price determinants, their results are open to research, although they cannot be fully clarified. In short, although there are many factors that affect price determinants, we are planning to use basic factors such as distance to shopping centers, ease of transportation and rental policies in our project process. The main purpose of using these basic elements is to respond to the changing needs of countries by producing similar policies regarding price determinants.

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