**University of Thessaly**
**Department of Economics**

# The value of trust on the Sharing Economy: Case Study of Airbnb in Athens

**Grigoriou I. Georgios**

**Department of Economics, University of Thessaly**
**email: gegrigoriou@uth.gr**

**SUPERVISOR**

Paschalis A. Arvanitidis
Associate Professor of Institutional Economics
Department of Economics, University of Thessaly
email: parvanit@uth.gr

**Volos, Magnesia, Greece**
**September 2018**

# Abstract

Sharing economy constitutes an innovative and novel way of providing goods and services to interested parties without middlemen. Perhaps the most important element of this new perspective is the development of the sharing behavior itself, which is predicated on trust. A well-known sharing-economy model specialized in hospitality services is Airbnb, a peer-to-peer platform and social network that enables people (hosts) to share their space with other people (guests) in exchange for a price. The current research focuses on the issue of trust in sharing economy in general and in Airbnb in particular. It aims to assess first the role that trust and reputation play in the development of rental price of Airbnb housing accommodations, and second to explore what determines hosts' trust to prospective guests. The Athens' house Airbnb market is used as a case study. Drawing on a sample of 311 houses rented through Airbnb in central Athens, the study uses, first, hedonic modelling to determine the shadow price of trust and reputation attributes and to assess the effect of other determinants of renal price, and second, Logit models to articulate what influence hosts' trust towards guests. It finds, first that having a verified ID (an indication of low trust) affects rental price negatively, and second, that only "good" or "positive" experience with the Airbnb model of sharing economy tends to increase trust to peers.



**Key words:** Airbnb, Hedonic price model, Trust, Athens

# Περίληψη

Η οικονομία διαμοιρασμού αποτελεί έναν νέο και καινοτόμο τρόπο παροχής προϊόντων και υπηρεσιών, χωρίς μεσάζοντες. Το σημαντικότερο, ίσως, στοιχείο αυτής της νέας οικονομίας είναι η ανάπτυξη της ίδιας της συμπεριφοράς και νοοτροπίας του διαμοιρασμού, η οποία βασίζεται στην εμπιστοσύνη. Ένα κοινώς γνωστό μοντέλο της οικονομίας διαμοιρασμού, το οποίο εξειδικεύεται κυρίως στις υπηρεσίες φιλοξενίας είναι η Airbnb, μια πλατφόρμα ομότιμων χρηστών και ένα κοινωνικό δίκτυο που επιτρέπει στους ανθρώπους (οικοδεσπότες) να μοιραστούν τον χώρο τους με άλλους (φιλοξενούμενους), σε μια προσυμφωνημένη τιμή. Η παρούσα έρευνα εστιάζει στο ζήτημα της εμπιστοσύνης στα πλαίσια της οικονομίας διαμοιρασμού και συγκεκριμένα στα πλαίσια της πλατφόρμας Airbnb. Στόχος αυτής της έρευνας είναι αρχικά η εκτίμηση του ρόλου που διαδραματίζει η εμπιστοσύνη και η φήμη στη διαμόρφωση των τιμών ενοικίασης των καταλυμάτων Airbnb και έπειτα η διερεύνηση των παραμέτρων που καθορίζουν την εμπιστοσύνη των οικοδεσποτών στους υποψήφιους επισκέπτες. Ως μελέτη περίπτωσης χρησιμοποιείται η αγορά κατοικίας της Airbnb στην Αθήνα. Χρησιμοποιώντας ένα δείγμα 311 κατοικιών που διατίθενται μέσω Airbnb και που βρίσκονται στις κεντρικές περιοχές της Αθήνας, η έρευνα αυτή εφαρμόζει αρχικά μοντέλα ηδονικής τιμολόγησης για να καθορίσει τις σκιώδεις τιμές των χαρακτηριστικών εμπιστοσύνης και φήμης αλλά και για να εκτιμήσει την επίδραση και άλλων καθοριστικών παραμέτρων στην τιμή ενοικίασης, και έπειτα με χρήση υποδειγμάτων Logit να προσδιορίσει τους παράγοντες που επηρεάζουν την εμπιστοσύνη των οικοδεσποτών προς τους φιλοξενούμενους. Τα δύο κυριότερα ευρήματα είναι, πρώτον, ότι χαμηλά επίπεδα εμπιστοσύνης από τη μεριά των οικοδεσποτών (ως ανάγκη να διαθέτουν ένα πιστοποιημένο προφίλ) φαίνεται να έχουν αρνητική επίδραση στην τιμή, και δεύτερον ότι η «θετική» εμπειρία στην Airbnb τείνει να αυξήσει την εμπιστοσύνη στους συναλλασσόμενους.


**Λέξεις κλειδιά:** Airbnb, Ηδονικό μοντέλο τιμολόγησης, Εμπιστοσύνη, Αθήνα

# Acknowledgements

I would like to express my gratitude to several individuals whose input has been invaluable for this work. Firstly, I would like to thank Paschalis Arvanitidis for contributing with his expertise and advice as a tutor. Secondly, I much appreciate the diligence of Panagiotis Manetos for the estimation of the geographical data of this study. Finally, I would like to thank my family – Valerie, John and Philip – for their support during my studies.

# Contents

# Chapter 1: Introduction

The term “sharing economy” refers, according to Lessig (2008 p. 143) who popularized the term in its current use, to “collaborative consumption made [*possible*] by the activities of sharing, exchanging and rental of resources without owning the goods”. Thus, sharing economy constitutes a new way of providing goods and services to interested parties by enabling people to share resources in creative and innovative ways, usually without middlemen (Cohen and Kietzmann 2014). The basis and drivers of these developments are attributed to the advancement of information technologies and social media in particular, which enable efficient (online) interaction between interested parties (Heinrichs 2013). Sharing economy takes many facets. For instance, people can share with others and stay in accommodations (e.g. Airbnb, Roomorama), be transferred by cars and bikes (e.g. Relay Rides, Wheelz) and enjoy taxi services without intermediaries (like Uber, Lyft) (Malhorta and Van Alstyne 2014).

Perhaps the most important element of sharing economy is the development of the behavior of sharing itself, which, by diluting interpersonal boundaries, brings people closer to each other and promotes cooperation and collective consumption (Belk 2010). Certainly, sharing economy is predicated on trust; this is the most debated word about the sharing economy (Nesta 2015). However, trust as a concept has many dimensions and perspectives (Arvanitidis and Nasioka 2017). With specific reference to the sharing economy these are: trust in peers, trust in the medium (platform, social media) and trust in other targets, from consumer’s, provider’s and both consumer and provider’s perspective (Hawlitschek et al 2018). Furthermore, trust can be divided into visual based trust (i.e. photos) and text based trust (such as reviews) (Ert et al 2016).

A well-known sharing-economy model specialized in hospitality services is Airbnb, a peer-to-peer platform and social network that enables people (hosts) to share their space with other people (guests) in exchange for a pre–agreed price. Airbnb brings users and providers of space in touch, introducing an alternative way of obtaining accommodation and travel experience in comparison to the traditional way (i.e. hotels). To this day, more than 4 million Airbnb listings have been offered in more than 191 countries (Airbnb.com 2018).

A major factor that motivates guests to use Airbnb is economic benefits, that is, the high added value (relative lower costs) (Guttentag 2016, Tussyadiah and Pesonen 2016) and the increased income for hosts (Hawlitshek et al 2016). However, Airbnb, as all facets of sharing economy, is heavily dependent on trust. Mittendorf (2016), for instance, establishes that trust in renters significantly affects provider’s intentions to offer their accommodation and to accept a booking request.

On the basis of the aforementioned, the aim of this research is the exploration of the key determinants of the rental prices of Airbnb listings, placing emphasis on the role of hosts' reputation and trust towards guests. The Athens' Airbnb market is used as a case study. To do so the study employs a hedonic pricing methodology that, *inter alia*, enables a 'shadow price' of trust and reputation to be assessed (of course for participants in the Athens' Airbnb market at the time the study takes place).

For the achievement of these objectives, the current work is consisted of two parts (Study 1 and Study 2). Study 1 evaluates the determinants of per night rental prices of Airbnb houses in Athens and focuses on how the trust and reputation attributes (non–visual based attributes, measured by the number of reviews and the average review score) affect these prices. This part aims to enrich the literature on rental value determinants of Athens' Airbnb listings, by identifying which characteristics may increase or decrease the value of an Airbnb listing and suggesting (implicitly) a price strategy to hosts in order for their listing to have a competitive price in comparison with the rest of the market. The second part (Study 2) firstly conceptualizes and quantifies the trust-in-peers concept, from the perspective of providers (that is, trust of hosts in prospective guests), and secondly investigates the aspects that determine this kind of trust. This second study aims to expand our knowledge with regard to trust hosts place in prospective guests, essentially focusing on the core of Airbnb culture and of the sharing economy in general. To do so the study uses information on the full set of 311 Airbnb housing listings, that were offered by hosts in central Athens on 9/5/2017 (available from opendata.com).

The rest of the dissertation is organized as follows. Chapter 2 outlines the hedonic pricing methodology and reviews the literature that employ such techniques to analyze aspects of the Airbnb model and the role of trust in the sharing economy. The description of the methodology that the current study follows (plus the research hypotheses and the description of variables used) are analyzed in Chapter 3. In Chapter 4 the analysis and results (descriptive statistics and results of the models) of Study 1 and Study 2 are presented. The conclusions of our study are outlined in Chapter 5, which also points out the added value and the limitations of this work.

# Chapter 2: Literature Review

This chapter outlines the literature review on the topics examined by the dissertation. These are: hedonic price modeling, Airbnb, price determinants of Airbnb accommodations and trust and reputation in the sharing economy. More specifically, section 2.1 focusses on hedonic pricing modeling discussing the theory of hedonic prices and the forms that these models take. Section 2.2 moves to Airbnb. After a general description of the Airbnb business model, it outlines the studies that have been concerned with the motives behind the adoption of the Airbnb, the impact of Airbnb in the housing market and the reason why Airbnb can be seen as a 'disruptive innovation'. Section 2.3 sheds light on the attributes that determine the rental prices of the Airbnb accommodations, and, finally, section 2.4 investigates the aspects and the importance of trust in sharing economy.

## 2.1 Hedonic price models

The housing commodity is comprised of many characteristics, which potentially contribute to its price. Hedonic price theory explains why this is the case, and hedonic regression analysis is used for the estimation of the marginal influence of these characteristics on the total value of a property.

The hedonic price theory articulates that the price of a product can be considered as a function of its characteristics or of the countable attributes that influence utility (Rozen 1974). In the context of housing such characteristics (or variables) include the attributes of the property (e.g. lot size, number of rooms, age of building and others), the neighborhood characteristics (urban utilities and services, population destiny, etc.) and the location qualities (distance to the central business district, education facilities, transportation hubs, etc.). Usually the size of the property (lot size, number of rooms, etc.) has a positive impact on price but the age has negative. The more utilities and services, the higher the price, but the larger the population density in the neighborhood, the lower the price. The small distance to a central business district (CBD), the existence of education facilities and transportation hubs affect the price positively.

In the theoretical front, Houthakker (1952) and Tinbergen (1956) made the first attempts to lay down a conceptual basis of the hedonic model. However, it was Lancaster (1966) who formulated a consumer-behavior theory oriented toward the demand for heterogeneous goods with objectively assessable and identifiable attributes. Lancaster (1966) was therefore the first who wrote about hedonic utility, but not on the hedonic price models.

Court (1939) is considered to be the father of the hedonic price methodology. However, there have been a few studies before him that examined the value of a good from a similar perspective. For example, Haas (1922), Wallace (1926) and Waught (1928) analyzed the price of a good as a function of the product quality, which would be measured by the product's attributes and their implicit prices.

Griliches (1961, 1971) introduced hedonic analysis techniques based on regression. Grilinches considers that the hedonic price approaches are based on the research strategy that assumes that a big number of models of a heterogeneous product can be included in terms of a smaller number of characteristics or factors. He simply states that:

$$P = f\,(C)$$

where P is the selling price of a property and C is a total value of factors which determine the price.

Hedonic pricing models are widely used in many fields of economics, including the following: real estate (Goodman 1978, García-Pozo 2009, Small and Steimetz 2012), impact of environmental factors on house prices (Kuminoff et al 2010, Nelson 2004), the labor market (Flabbia and Maroc 2012, Goldhaber et al 2010), the tourism and its subsectors (accommodation, catering, passenger transport, travel agents, and leisure) such as price competitiveness of tourism packages (Aguiló et al 2005, Mangion, et al 2005, Taylor 1995), urban hotels (Chen and Rothschild 2010, Thrane 2007; Zhang et al 2011), holiday area hotels (Abrate et al 2011, Espinet et al 2003, Fleischer 2012), holiday apartments (Juaneda et al 2011, Portolan 2013, Saló and Garriga 2011), and bed and breakfasts (Monty and Skidmore 2003).

### 2.1.1 Theory of the hedonic price model

Rozen (1974) was the first to present the hedonic price theory arguing that the total price of a good equals to the sum of prices of its features. Rosen (1974) provided the hedonic methodology with microeconomic fundamentals that made it suitable for formalizing empirical contributions. From that time onward, the model developed by Rosen was widely accepted.

Rozen (1974) sketches a model of product differentiation based on the hedonic hypothesis that goods are valued for their utility-bearing attributes or characteristics. Hedonic prices are defined as the implicit prices of attributes and are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them. Rozen provides a generating mechanism for the observations in the competitive case and uses that structure to clarify the meaning and interpretation of estimated implicit prices. The model suggests a method that often can identify the underlying structural parameters of interest.

Also, as a general methodological point, it is demonstrated that conceptualizing the problem of product differentiation in terms of a few underlying characteristics instead of a large number of closely related generic goods leads to an analysis having much in common with the economics of spatial equilibrium and the theory of equalizing differences.

The model itself amounts to a description of competitive equilibrium in a plane of several dimensions on which both buyers and sellers locate. The class of goods under consideration is described by n objectively measured characteristics. Thus, any location on the plane, is represented by a vector of coordinates $z = (z_1, z_2, \ldots z_n)$, with $z_i$ measuring the amount of the $i^{th}$ characteristic contained in each good. Products in the class are completely described by numerical values of z and offer buyers distinct packages of characteristics. Furthermore, existence of product differentiation implies that a wide variety of alternative packages are available. Hence, transactions in products are equivalent to tied sales when thought of as bundles of characteristics, suggesting applicability of the principle of equal advantage for analyzing market equilibrium.

In particular, a price $P(z) = P\ (Z_1, Z_2, \ldots Z_n)$ is defined at each point on the plane and guides both consumer and producer locational choices regarding packages of characteristics bought and sold. Competition prevails because single agents add zero weight to the market and treat prices P(z) as parametric to their decisions. In fact, the function P(z) is identical with the set of hedonic prices "equalizing differences", and is determined by some market clearing conditions: amounts of commodities offered by sellers at every point on the plane must equal amounts demanded by consumers choosing to locate there. Both consumers and producers base their locational and quantity decisions on maximizing behavior, and equilibrium prices are determined so that buyers and sellers are perfectly matched. No individual can improve his position, and all optimum choices are feasible. As usual, market clearing prices, P(z), fundamentally are determined by the distributions of consumer tastes and producer costs.

### 2.1.2 Forms of hedonic price models

Although the hedonic function that equates the price of a property in relation to its attributes can take many forms, the fundamental form is:

$$P = f\,(S, N, L, C, T)$$

Where P is either selling or rental price, S is the constructional features of property, N the neighborhood features, L the location attributes, C the characteristics of the contract, T the time price is observed (Malpezzi 2003). For the estimation of the characteristics which mostly influence the price of a heterogeneous such product, the use of multiple regression analysis is applied.

Generally, the typical forms of hedonic price regression models are the following:

**Linear specification:** both dependent and explanatory variables enter the regression with linear form:

$$P = \beta_o + \sum^{\kappa}_{\kappa=1} \beta_\kappa x_\kappa + \varepsilon$$

Where P is the property price, ε is a vector of random error term and $\beta_k$ (k = 1, …, K) indicates the marginal change of the unit price of the $k^{th}$ characteristic $x_k$ of the good.

**Semi-log specification:** in a regression analysis, dependent variable takes log form and explanatory variables are linear or dependent variable is linear and explanatory variables take log form:

$$LnP = Ln\beta_o + \sum^{\kappa}_{\kappa=1} \beta_\kappa x_\kappa + \varepsilon$$

Where P is the property price, ε is a vector of random error term and $\beta_k$ (k = 1, …, K) indicates the marginal change of the unit price of the $k^{th}$ characteristic $x_k$ of the good.

**Log – log specification:** in a regression function, both the dependent and explanatory variables take log form:

$$LnP = Ln\beta_o + \sum^{\kappa}_{\kappa=1} \beta_\kappa Lnx_\kappa + \varepsilon$$

Where P is the property price, ε is a vector of random error term and $\beta_k$ (k = 1, …, K) indicates the marginal change of the unit price of the $k^{th}$ characteristic $x_k$ of the good.

**Box – Cox transform:** determine the specific transformation from the data itself then enter the regression in individual transformed form:

$$P(\theta) = \beta o + \sum^{\kappa}_{\kappa=1} \beta_\kappa (x_\kappa)^{(\lambda\kappa)} + \varepsilon$$

Where,

$$P^{(\theta)} = (P^{(\theta)} - 1)/ \theta \ , \quad \theta \neq 0$$

$$= LnP \ , \quad \theta = 0$$

$$x^{(\lambda\kappa)} = x^{(\lambda\kappa)} / \lambda\kappa \ , \quad \lambda\kappa \neq 0$$

$$= Lnx_\kappa \ , \quad \lambda\kappa = 0$$

If the θ and $\lambda_\kappa$ are to equal 1, the equation transforms to the linear form. If the θ equals to 0, the model transforms to the log – linear form. If the θ equals to 0 and $\lambda_\kappa$ are equal to 1, the model takes the semi – log form (Malpezzi 2003).

## 2.2 Airbnb

In this section we present some general information about Airbnb, we explain one's motives to use the Airbnb services, we show the impacts of Airbnb in housing markets and also discuss trust in the context of the sharing economy.

### 2.2.1 What Airbnb is

Airbnb was founded in 2008 in San Francisco (Airbnb 2018a). Airbnb is a global travel community that offers peer to peer accommodation, experiences (entertainment, trips, social interaction, sports) and food, and charges service fees to participants (hosts and guests). Airbnb's accommodation marketplace is spread in more than 191 countries and it contains apartments, houses, private rooms, villas, castles, treehouses and bed and breakfasts (B&B) (Airbnb 2018a).

The Airbnb website works with the following procedure: based on destination, dates, property type and number of guests, a guest searches for an accommodation. Then, the website returns the listings – spaces accompanied with characteristics like price, property type, maximum number of guests, reviews and some photos of the accommodation. If the prospective guest selects an accommodation, he is able to see more details about the specific listing. Lastly, if the listing corresponds to guest's desires, he can make a reservation.

Airbnb targets to property hosts and travelers. Target groups are adventure-seekers, city-breakers, people who would like to travel and people who would like to earn extra income by offering their apartments for a short term (Le Jeune 2016). The fee for home host service is generally 3%, but may be higher for hosts in Italy or hosts who have a "super strict" cancellation policy, whereas the corresponding fee for guest service ranges between 0% and 20% according to factors like the reservation subtotal, the length of the stay, the characteristics of the listing, etc. (Airbnb 2018b).

The following statistics and facts provide an indication of the size and importance of Airbnb (see also Table 1 and Figure 1): Airbnb's total valuation is $31 billion, the number of Airbnb users is 150 million, the number of Airbnb hosts is 640 thousand, the number of Airbnb listings is more than 4 million, and the total guest arrivals are 300 million since 2008 (Smith 2018).

| |
|---|
| 1. In 2008, roughly 400 guests checked into in Airbnb listings. Now, 400 guests check in to Airbnb listings every two minutes. |
| 2. Airbnb guests spent $6.5 billion in restaurants in 44 cities around the world from September 2016 to September 2017 |
| 3. In 2008, roughly 400 guests checked into in Airbnb listings. In 2018, 400 guests check in to Airbnb listings every two minutes. |

| |
|---|
| 4, Airbnb hosts have earned $41 billion in 10 years |

Table 1: More facts about Airbnb. Source – IOL 2018

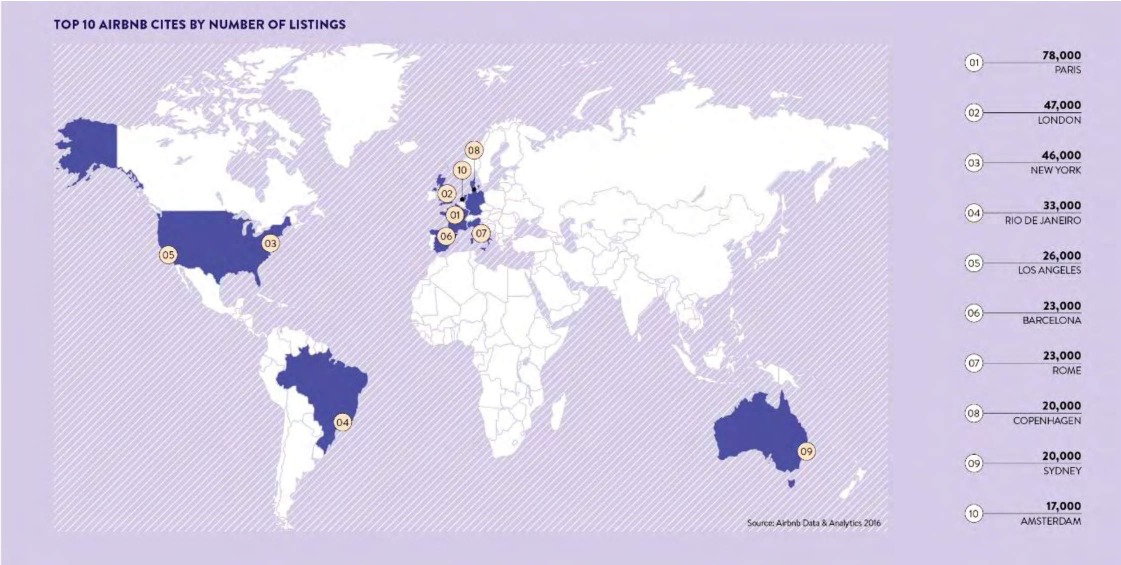



Figure 1: Top 10 cities by number of Airbnb listings (Source Airbnb Data & Analytics 2016)

Airbnb is becoming an important player in the accommodation markets. Airbnb is a self-defined "community marketplace" directly connecting hosts and consumers in a short-term rental economy outside of the traditional rental industries (such as hotels or B&Bs). Peer to peer accommodation sharing is mostly used by tourists seeking affordable accommodations in popular tourist destinations (Pizam 2014).

Research on Airbnb is very recent and focuses on the motivations for its use (Tussyadiah and Pesonen 2016, Satama 2014, Yang and Ahn 2016, Mao and Lyu 2017, Guttentag 2016, So et al 2018), host's performance (Li et al 2015), host's motivation for listing their property on Airbnb (Ikkala 2014), user satisfaction (Ert et al 2015, Fradkin et al 201, Zervas et al 2015), impacts of Airbnb on the hotel industry (Zervas et al 2017, Neeser et al 2015, Choi et al 2015) while others explored the influence on employment of the tourism industry (Fang et al 2016). Other aspects of Airbnb that have been examined are legal issues (Edelman and Geradin 2015, Lee 2016), the Airbnb platform system (Fradkin et al 2014, Ert et al 2015) and repurchase intentions (Liang et al 2017).

### 2.2.2 Drivers and deterrents of the adoption of Airbnb

There are several studies which have examined possible motivations for someone to use Airbnb. Most of them agree that price, value or, generally, economic benefits (more value with less cost) are a major factor that motivates guests to use Airbnb (Tussyadiah and Pesonen 2016, Satama 2014, Yang and Ahn 2016, Mao and Lyu 2017, Guttentag 2016, So et al 2018).

Authenticity is another factor that drives guests to stay in an Airbnb accommodation. Studies such as Liang (2015), Guttentag et al (2017), Poon and Huang (2017) and Mody et al (2017), provide the relevant discussion and evidence, whereas authenticity, in the frame of Airbnb, concerns the “real experiences” of staying at an Airbnb accommodation.

Moreover, “unique experience” (Mao & Lyu 2017) or novelty, defined as the degree to which a customer desires to obtain information or experiences about new products (Maning et al 1995), is a factor that motivates certain people to stay at an Airbnb accommodation (Guttentag 2016, Johnson and Neuhofer 2017, Mao and Lyu 2017). These people are called “novelty seekers” (Guttentag 2016).

Tussyadiah and Pesonen (2016) also identified social appeal, that is the desire for community engagement (collaborative consumption offers opportunities to create and maintain social connections and a sense of community) and the desire for sustainability (collaborative consumption reduces the development of new products and the consumption of raw materials), as important factors leading people to use P2P accommodation sharing. Social interactions is a motive for a P2P stay (Guttentag 2016, Johnson and Neuhofer 2017, Camilleri and Neuhofer 2017, Poon and Huang 2017, Mody et al 2017, and Tussyadiah and Pesonen 2016, So et al 2018).

Other incentives are enjoyment or hedonic motivations, that is the fun or pleasure derived from the use of the specific service (Tussyadiah and Pesonen 2016, Satama 2014, So et al 2018) and home benefits related to attributes of a property, such as amenities offered, homely feel and large space (Guttentag 2016, Johnson and Neuhofer 2017, So et al 2018). Sharing economy ethos also constitutes a motive for a prospective guest to use Airbnb accommodation, which means guest’s willingness to spend their money on local, friendliness, non-professional accommodation (Guttentag et al. 2017). Moreover, familiarity or unfamiliarity (a person’s feelings based on previous experience) constitute an incentive and deterrent respectively (Mao and Lyu 2017, Tussyadiah and Pesonen 2016).

Hawlitschek et al (2016b) developed a questionnaire (addressed to students at the Karlsruhe Institute of Technology, more than 600 participants) for the assessment of the motives for and against participating in the sharing economy. By applying factor analysis, the researchers found that major motives for both consumers and providers are the following: enjoyment, the idea that sharing expresses a modern life style, the idea that sharing offers a wide range of different products and services, the idea that one feels as part of a sharing community, the idea that sharing enables social experience, the idea that one's social environment appreciates sharing, the idea that sharing may save money. The motive for providers is the idea that sharing may generate an (additional) income and the deterrents are the idea that resources may not be available when trying to access them through sharing and the idea that ownership is associated with social prestige. The incentives for users are the anti-capitalism idea and the idea that sharing allows to access products and services in many places.

Perceived risk, the feeling of uncertainty in using the service, the lack of trust from guests towards hosts, the lack of trust in technology and the lack of trust toward the company (Satama 2014, Liang 2015, Tussyadiah and Pesonen 2016, Mao and Lyu 2017, So et al 2018) constitute the deterrents of the consumer's adoption of Airbnb.

### 2.2.3 Impacts on the hotel industry and housing prices

Some previous studies have examined the impact of Airbnb on the hotel industry. Some of them have focused on hotel revenues (Choi et al 2015, Neeser et al 2015, Zervas et al 2017) and anothers in tourism industry employment (Fang et al 2016). Thus, Zervas et al (2017) found that a 1% increase in Airbnb listings in Texas resulted in a 0,05% decrease in the quarterly hotel revenues, whereas Fang et al (2016) showed that the sharing economy can generate employment and benefit the entire tourism industry (period of 2009–2013 in Idaho).

Other researchers examined the impact of Airbnb on the local housing markets. Barron et al (2016) studied the impact of Airbnb businesses on house prices and rental rates in the USA, using a dataset of Airbnb listings from all the country. Their results showed that a 1% increase in Airbnb listings leads to a 0.018% increase in rents and a 0.026% increase in house prices. Similarly, Eliason and Ragnarsson (2018) explored the impact of the Airbnb in the Icelandic housing market and found an increase of real house prices, estimated at 2% per year for the last three years, and about 15% since its inception. Likewise, Segu (2018) found that Airbnb is responsible for a 4% increase in rents for the city of Barcelona.

### 2.2.4 Airbnb as a disruptive innovation

Guttentag (2015) examined the potential of Airbnb to disrupt the traditional accommodation market through Christensen's disruptive innovation theory and identified Airbnb accommodation as a disruptive product. A disruptive innovation is the process of the development of new products and services which replace the existing technologies and gain a competitive advantage, shaking up a market (Bower and Christensen 1995, Christensen 1997).

Generally, the performance of disruptive products is weaker than that of the prevailing products, but disruptive products are usually cheaper and have some new benefits. In our case, Airbnb accommodation is usually cheaper than traditional services, and some of its benefits for guests is that they have the opportunity to live like locals and sometimes to stay with them (Guttentag 2015). However, service quality, staff friendliness and security are the attributes that partially lack in Airbnb, in comparison with hotels (Dolnicar and Otter 2003).

To sum up, Airbnb is a disruptive innovation that offers new hospitality services and experience mostly to tourists. Its appeal and popularity has been increased over the years and its business model has been spread to numerous countries worldwide. The major incentives for someone to stay in an Airbnb residence are the economic benefits, authenticity and novelty. It is observed that the development of the Airbnb market influence real housing prices in a rather positive manner.

## 2.3 Price determinants of Airbnb accommodations

The current section outlines the attributes that determine the rental prices of Airbnb accommodations according to previous studies.

The setting of prices for a traditional hotel is typically driven by the economic need for a business to gain profit. Managers have adequate information about the pricing strategies of their competitors, future supply of new accommodation and demand generators that allow them to set prices for optimal economic gain. Within Airbnb, the supply of accommodation is controlled by hosts who are mostly motivated by economic reasons (Gutt and Herrmann 2015, Lampinen and Cheshire 2016). These include, as Karlsson and Dolnicar (2016) argue, not only their desire for monetary gain and profit, but, in many cases, their need to cover fixed costs, such as taxes, bills and mortgage payments. To achieve these, Airbnb hosts can set rental rates on a daily, weekly or monthly basis, and as such to determine prices that change over short periods of time.

As it is argued above (section 2.2.2) economic benefits constitute a major motivation for someone to stay in an Airbnb accommodation, since Airbnb accommodations are generally cheaper than traditional hospitality accommodation like hotels (Guttentag and Smith 2017).

The factors that, according to the relevant literature, determine the rental price of Airbnb accommodations are as follows.

### *Property (structural) attributes*

Many researchers have shown that the price of an Airbnb listing is associated with accommodation’s structural attributes, like size and property type. Literature usually measures the size of an Airbnb accommodation by its capacity (accommodates/number of guests), the number of bathrooms, the number of bedrooms or the number of beds. It is established that prices are positively related to the size of the accommodation (Wang and Nicolau 2017, Zhang et al 2017, Ert et al 2016, Gibbs et al 2018, Teubner et al 2017, Magno et al 2017). Property type is also a fundamental factor that affects price. Wang and Nicolau (2017) and Magno et al (2017), amongst others, found that entire homes or apartments and private rooms are associated with higher prices instead of shared rooms. Ert et al (2016) showed that prices of entire homes/apartments are higher than those of rooms. A study of Airbnb listings in Canada (Gibbs et al 2017) found that entire apartments are priced 44.2% higher than private rooms. Teubner's et al (2017) concluded that entire homes affect the rental price of Airbnb accommodation positively.

### *Accommodation amenities*

Gibs et al (2017) showed that accommodation amenities like a pool, gym and private parking space, affect the price positively. Real beds, wireless internet, free public parking also tend to increase rental prices (Wang and Nicolau 2017). To our knowledge, there is no study that has examined if the existence of air-conditioning in an Airbnb property affects the rental price. Surprisingly, Wang and Nicolau (2017) found that offering a breakfast affects the price negatively. However, for Dogru and Pekin (2017) the amenity of free breakfast increases the rental price. Furthermore, they showed that availability of washing machine increases the price by 6%. The same authors found that if the accommodation is family friendly[1] then the rental price increases by 10%. Lee et al (2015) show that if pets are allowed, the prices get lower. The authors also identified that the availability of a gym and shampoo affect the price positively, but the existence of a kitchen, intercom and television affect the price negatively.

### *Location*

Generally, researchers agree that accessibility (i.e. short distance to location hubs) affects positively Airbnb listing prices. Zhang et al (2017) employed a sample of 974 listings in Metro Nashville, Tennessee, USA, found that the Euclidean distances to the Nashville Convention Center (km) and to nearest highway both have a negative impact on rental price (the longer the distance, the lower the price). Similarly, Teubner et al (2017) and Dogru and Pekin (2017) showed that the variable "distance to city center" also has a negative coefficient in relation to price. Gibs et al (2017), ended up with a similar result, since the distance from the property to

[1] A listing is family friendly when it fulfils requirements such as: entire home, the offering of a kitchen, availability of TV and Wi – Fi, and an 4.8 average rating score in the past 365 days with at least 5 total reviews.

the local city Hall has a negative impact on price. Li et al. (2016) supports that distance to nearest landmarks has a positive effect.

*Neighborhood / city attributes*

Neighborhood qualities such as levels of noise, pollution, crime rates, etc. are assumed to affect property prices. Teubner et al (2017) explores such attributes using the population density as a proxy. He finds that residential density (log-population) have positive effects on price.

*Contract terms and rules*

Contract terms and rules are expected to exert an effect on the rental price of accommodation. However, limited research has examined the impact of such attributes on Airbnb accommodations. Dogru and Pekin (2017) showed that the cleaning fee is associated with higher prices. Lee et al (2015) showed that the variable "minimum stay" affects the rental price negatively, but Teubner et al (2017) found no such statistical significance. The latter also found no statistical significance on the variable "Check in/out comfort", but in another study (Teubner et al 2017) they shown that if a deposit is required, prices are likely to be higher, something also verified by the study of Wang and Nicolau (2017).

In a similar sense, Teubner et al (2017) and Wang and Nicolau (2017), find that lower prices are likely to be associated with instant booking service (i.e. host does not need to confirm the reservation) but with strict cancelation rules, whereas requirements by hosts for guests to verify their phone would affect prices positively. Gibs et al (2018) also found a negative coefficient on the variable "instant booking".

*Host attributes*

Another factor, according to the literature, that determines rental prices of Airbnb accommodations is host's characteristics. Wang and Nicolau (2017), Teubner et al (2017), Gibs et al (2018) and Dogru and Pekin (2017) support that the status of "Superhost"[2] is related to higher rental prices. For Teubner et al (2017), Gibs et al (2018), Magno et al (2017) and Wang and Nicolau (2017) the number of listings that a particular host owns affects the price positively. According to Gibbs et al (2017), Wang and Nicolau (2017) and Teubner et al (2017), the higher number of host's pictures, the more the price charged. Another variable that has a positive coefficient for price is hosts' experience in the medium (i.e. how much time the host owns at least one Airbnb listing) (Teubner 2017, Magno et al 2017), but Lee et al (2015) showed that experience reduces the price. The ethnic or racial profile of hosts might also have an effect of

[2] To be a superhost someone has to maintained (1) a 50% review rate or higher, (2) a 90% response rate or higher, (3) a 4.8 overall rating and (4) to have no cancelations

the price they ask. Edelman and Luca (2014) find that non-black hosts in New York City charge higher prices than their black counterparts, whereas Kakar et al (2016) show that hispanic and asian hosts on average have a 9,6% and 9,3% lower list price respectively, relatively to white hosts.

*Reputation and trust attributes*

On the basis of the argument that the number of reviews effects heavily the prices of Airbnb accommodation (Hill 2015), Zhang et al (2017), Gibs et al (2017), Teubner et al (2017), Magno et al (2017) and Wang and Nicolau (2017) find a negative such relation. On the other hand, Ert et al. (2016) find no such statistical significance, not only for the number of reviews but also for the average customer rating. However, most of the literature agrees that the higher the customer rating is, the higher is the price (Gibbs et al 2017, Teubner et al 2017, Wang and Nicolau 2017). In fact, Gutt and Herrmann (2015) showed that an one point increase in rating leads to an increase in price by 2.69 euros.

Hosts' verified ID also seems to affect positively the rental price of accommodation (Wang and Nicolau 2017), though other studies (i.e. Teubner et al 2017) have showed the opposite.

*Other price determinants*

Market demand (total number of beds in bookable shared accommodations available on a specific date) is another price determinant. Specifically, the increase of one bed in the total number of bookable P2P property rentals on one date is correlated to an average increase of prices of 0.02% on that date (Magno et al 2017).

To conclude, the factors that influence the pricing strategies of the hosts are property attributes and amenities offered, neighborhood characteristics, the rules of the listings, and host attributes including reputation and trust. The next section focuses on these two last aspects.

## 2.4 Trust and reputation in Airbnb and the sharing economy

Previous studies have shown that trust is an important parameter for the establishment of business relationships in interpersonal and commercial environments (McKnight and Chervany 2001, Morgan and Hunt 1994). So is the case in Airbnb, and in the sharing economy model in general. However, trust has may dimensions in the context of sharing economy. A fundamental aspect of trust is the trust in peers, from consumer's, from provider's and both from consumer's and provider's perspectives. Another important aspect, though less explored in the literature, is trust in the platform. The current section draws on the work of Hawlitschek et al (2018) to explore all these aspects and issues.

Trust is the most often mentioned word when we discuss about the sharing economy (Nesta 2015). This is because, in online P2P marketplaces, two contracting parts (usually strangers between each other) are unlikely to make a transaction without trusting each other (Bonson Ponte et al 2015, Kim et al 2011). Due to asymmetric information and economic risks, reputation mechanisms have been developed to encourage trust among trading parties (Resnick and Zeckhauser 2002), since increased reputation seems to enhance trust (Ert et al 2016, Resnik et al 2006, Melnik and Alm 2002, Livingston 2005, Diekmann 2014, Resnik and Zeckhauser 2002, Jia and Wagman 2018). However, reputation should be rather seen as a condition for trust, because people sometimes trust strangers even without information on their reputation.

The most popular reputation mechanism in the sharing economy is the reviews made by previous users (guests). Airbnb endorses this mechanism, by aggregating customer reviews, connecting consumers' social networks to their Airbnb accounts, and acting as a secure payment intermediary.

### 2.4.1 Trust in peers

Trust in peers is the trust between consumers and providers. Aufmann (2016) stated that such trust (i.e. between hosts and guests) makes Airbnb possible. The trust in peers is consisted of consumer's, of provider's and of both consumer's and provider's perspective, which are discussed next.

*Consumer's perspective*

Trust is mainly assessed from the perspective of consumers (Papadopoulou et al 2001, Mohlmann 2015). Teubner et al (2017, 2016) consider trust of the consumer in terms of willingness to rely on the host's actions and intentions. Deng and Ravichandran (2017) suggests to differentiate between visual-based trust (photos) and text-based trust (reviews) in providers to analyze consumers purchasing behavior on Airbnb.

The affect-based factors, that Yang et al (2016) identified and expect to exist, are reputation (how users feel about Airbnb hosts by reading their personal information, rating, reviews, or Superhost recommendation), interaction (the extent to which Airbnb hosts and users experience interaction in the process of making a transaction, ongoing conversation or real-time feedback) and familiarity (the degree of agreement or preference that users find in similar interests, values, or lifestyles with Airbnb hosts).

Ert et al (2016) and Ert and Freischer (2017) studied the effects of photos, facial and image characteristics on the trustworthiness of Airbnb hosts. They measured trustworthiness, asking "How trustworthy is this person", in a 10-point Likert scale, to find that consumer's choice are affected by product attributes (e.g. apartment size, location) and seller attributes (reputation, visual appearance - photo). Moreover, host photos play a significant role even when reputation varies. Visual (host photos) and nonvisual (reputation, reviews) information has positive effects in trust building.

Mohlmann (2015) applied partial least squares path modeling analysis on 187 Airbnb users and found that trust affects satisfaction with a sharing option positively. Ma et al (2017) measured hosts' trustworthiness by developing a six-item perceived trustworthiness scale on three dimensions: ability (capability of paying rent or mortgage, and maintenance of a clean, safe, and comfortable household), benevolence (host's concern for satisfying guest needs during stay, willingness to go out of their way to help guests in case of an emergency during stay) and integrity (the degree to which a host sticks to their word, and do not intentionally harm, overcharge, or scam their guests). The authors found that the hosts who have longer self-descriptions are perceived to be more trustworthy.

Wu et al (2017) using regression analysis in a sample of 1345 hosts on xiaozhu.com (corresponding website of Airbnb in China) in Beijing examined the effects of host's perceived trustworthiness on consumer's booking behavior (measured by orders that hosts receive). Host trustworthiness was measured in three dimensions, named benevolence (host's average response rate, host's average confirm time), ability (host's acceptance rate of order, number of houses host owns) and integrity (host personal page open or not). The authors found the following variables statistically significant with positive coefficients: host's average response rate, host's acceptance rate of order, number of houses that host owns, host personal page open or not. They also found that consumers prefer to choose women as hosts when they book a single room.

Han et al (2016) investigate how trust in the Airbnb platform affects trust in hosts, given a certain fit of user, platform and host characteristics. Airbnb and host characteristics are seen as determinants of perceived fit (between Airbnb and host characteristics) in the sharing economy. Perceived fit also influences trust in Airbnb platform and trust in hosts. Lastly, trust in Airbnb transfers to trust in hosts.

### *Provider's perspective*

The trust in consumers from the accommodation provider's perspective is assessed with contextual measurement approaches. Mittendorf (2016) investigated the concept of trust both in the accommodation platform (Airbnb.com) and in potential guests. A questionnaire was designed and 189 participants answered in a 7-point Likert scale (1-strongly agree, 7-strongly disagree) whether they "trust renters" in accordance to the following aspects: renters are in general reliable, renters are in general honest, I trust potential renters, I believe renters are trustworthy. The results showed that both respondents' deposition to trust in general and to trust in Airbnb in particular affect host trust in renters. They also found that both trust in the Airbnb platform and trust in renters affect provider's intentions to offer an accommodation and to accept a booking request. A study that examines the Airbnb platform (Mittendorf and Ostermann 2017) distinguishes trust in business and trust in private customers, by investigating how trust, social motives and perceived risk alter the accommodation provider's intentions to accept a booking request.

Abramova et al (2015) examined the role and effect of negative reviews in P2P accommodation provision, using 82 listings in New York and 200 listings in Milan as a case study. By applying regression analysis they showed that customer trust after negative reviews can be improved if the host endorses either a confession/apology or a denial strategy, with the former being the most effective one.

*Consumer's and provider's perspective*

The studies which examine both consumer's and provider's trust in peers use the same measurement instruments to both parties. Kamal and Chen (2016) explored the factors that have an impact on people's trust and willingness to participate in the sharing economy. They concluded that the sharing economy is still at an early stage and that the major obstacle in the sharing economy is lack of trust between sharing members. The top three risk factors found from participants' answers are risk of life loss, theft and loss of property.

Hawlitschek et al. (2016b) investigate the lack of trust in other users as one of 24 potential drivers and impediments for participation in peer-to-peer rental. They find that lack of trust (the idea that other sharing users should not be trusted) which mixes with process risk (the idea that sharing involves procedural risks) is a major deterrent for using the sharing economy for both users and providers.

Chica et al (2017) present an evolutionary trust game to investigate the formation of trust in the so-called sharing economy from the general population perspective. Untrustworthiness of the consumers (e.g. causing financial and/or psychological costs to the provider due to theft or damage) is reciprocated with untrustworthy behavior by the providers (e.g. deviating from the agreed upon level of access to the asset), driving consumers to behave untrustworthily. Likewise, trustworthiness can also be reciprocated and relayed between consumers and providers. So, this balancing effect, stemming from the high level of mutual trust required between the consumer and the provider, drives higher welfare levels in the sharing economy.

### 2.4.2 Trust in the platform

The cognitive-based factors, that Yang et al (2016) identified and expect to exist, are security and privacy (how well personal information is used and protected before and after making a transaction), IT quality (how Airbnb users feel about using the website including aspects such as ease of use, controllable, intuitive to find sources, and website design and effects) and Airbnb traits (the extent to which an Airbnb accommodation has its unique characteristics in addition to the traditional hotel accommodation).

Drawing on Ba and Pavlou (2002), Kim et al (2015) assert that trust in the platform is a direct antecedent of intention to participate in the sharing economy and suggest to measure such trust along the lines of platform's honesty, reliability and competence.

Philip et al (2015) support that trust in a P2P network (such as Airbnb) depends on the risk of use (i.e. fear of negative reciprocity, the high involvement nature of the transaction).

Instead of examining trustworthiness and trusting beliefs, Liang et al (2018) argue the need to differentiate between two other dimensions of trust: institution-based trust (trust in Airbnb) and deposition to trust (trust in hosts). To that end, they designed a questionnaire that they address to Airbnb users, and they used confirmatory factor analysis (CFA) and structural equation modeling (SEM) to examine how some aspects affect these kinds of trust. The results demonstrate that transaction-based satisfaction (i.e. satisfaction with the recent transaction experience with Airbnb, and satisfaction with the overall mechanism of Airbnb) has both direct and indirect effects on repurchase intention, trust in hosts and switching intention, while it has a direct effect on trust in Airbnb. The authors conclude that satisfaction with Airbnb can be assessed based on the transaction and the experience process as well as trust in the Airbnb company and its hosts.

Philip et al (2015) support that trust in P2P network (such as Airbnb) depends on the risk of use (fear of negative reciprocity, the high involvement nature of the transaction). Teubner and Hawlitschek (2018), by reviewing studies about trust in sharing economy, conclude to different means of building trust between providers, consumers and the platform (i.e., verification and signaling, ratings and reviews, insurances and support, web design, and user representation).

To sum up, trust in the sharing economy in general and the Airbnb in particular, is a major aspect for its development. However, trust and reputation are difficult to build and to maintain because there are a lot of risks and asymmetries that arise (principally in information) between those involved. To that end, scholars have pointed out specific strategies that peers can deploy in order to build trust in each other. Some suggestions to hosts seeking to enhance trust, on the part of perspective guests, are to provide comments (in a form of explanations or an apology) to negative reviews and to publish more visual (and not only) information (such as photos) so that the aforementioned asymmetries to be somewhat mitigated. Finally, the trust of hosts to the potential guests affect the providers' intentions.

# Chapter 3: Methodology

This chapter describes the methodologies that we follow about our two topics. The Section 3.1 describes the methodology of Study 1. Section 3.1.1 refers to the OLS method theoretically and Section 3.1.2 describes the research model and the hypotheses that we developed in Study1. In Section 3.2 the methodology of Study 2 is presented. Section 3.2.1 is refered to the theory of the Logit model and in Section 3.2.2 we describe the research model and the hypothesis development of Study 2.

In total, there are 5127 Airbnb listings located in the center of Athens, from which 83,2% (4268) are entire houses/apartments, 15,8% (808) are private rooms and 1,0% (51) are shared rooms (Insideairbnb.com). The average rental price per night is 55 euros. Airbnb guests may leave a review after their stay and these can be used as an indicator of Airbnb rental activity. The estimated reviews/listing per month is 1,5 and the estimated income of hosts per month is 382 euros (insideairbnb.com). Airbnb established its presence in Athens in 2011, since the total Airbnb rentals the year before (in 2010) were none but in that year (2011) they reached to 133 (airdna.com).

Our study was carried out in spring 2018 and is based on secondary data collected from the websites public.opendatasoft.com and insideairbnb.com. A total of 311 Airbnb accommodation listings (of which 75,72% are entire houses and 24,28% are private rooms) in the center of Athens constitute the sample of the study, since these properties were those that were available at the date the data set was compiled, which is the 9$^{th}$ of May 2017. Study 1 examines the key variables that influence the rental price of these 311 Airbnb listings (houses). We developed a series of OLS (Ordinary Least Squares) hedonic pricing models to examine a number of research hypotheses set. Study 2 focuses on the key variables that determine the trust of hosts (of those 311 Airbnb listings) toward prospective guests. To do this we employ Logit (Logistic regression) models. The listings used in our analyses are shown on the following map (Figure 2). The descriptive statistics of both studies were conducted by using Excel, and the analyses and diagnostic tests of the models were performed by Eviews 9 Student version.

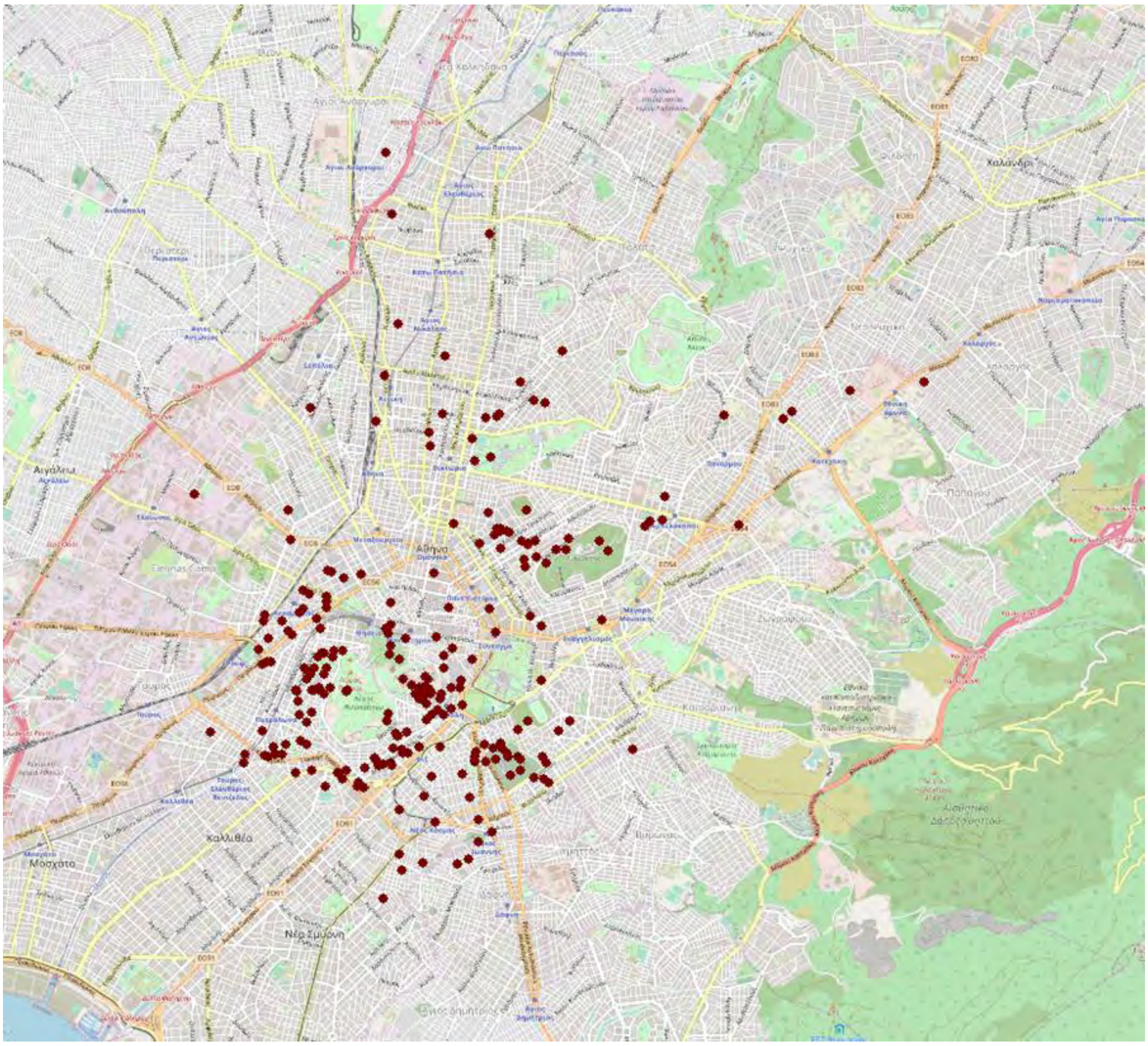


Figure 2. Distribution of the 311 Airbnb housing accommodation listings in Athens (author's construction)

The methodologies of Study 1 and Study 2 are discussed further in sections 3.1 and 3.2 that follow respectively. In each one we firstly describe the general theories of the models that are applied, secondly we present the variables, thirdly we outline our hypotheses and lastly we present the theoretical models.

### 3.1 Methodology of Study 1

This study (Study 1) examines the key variables that determine the price of an Airbnb listing and focuses on how reputation and trust attributes (measured by the number of reviews and the review score) affect rental prices. Hedonic price analysis is performed on the Airbnb housing market at the center of Athens, and we present three of a series of OLS models developed

(OLS1, OLS2 and OLS3). As discussed, our initial sample is consisted of 311 Airbnb listings. However, the sample in all of the hedonic models is reduced to 256 listings, of which adequate information was available. Alongside, the diagnostic tests of heteroscedasticity (White's test), multicollinearity (Variance Inflator Factors) and regularity of residuals (Jargue Bera's test) are performed and are presented in the Appendix.

### 3.1.1 The Ordinary Least Squares (OLS) method

According to Halkos (2011), the ordinary least squares method (OLS) is used for the selection of the best linear relation between the variables of a model. However, the relationship between the variables may not always be accurate. Practically, the random or not observed variations on the observations may lead to false results. For including these variations, a stochastic – random part is added in the regression model. If we use the variable X, to interpret the behavior of Y, our model takes the form:

$$Y_i = \beta_o + \beta_1 X_i + \varepsilon_i$$

where, $\beta_o + \beta_1 X_i$ is the systematic part of the equation, and $\varepsilon_i$ is the random part, known as residuals. To estimate the parameters of the model, at first we collect a sample of observations that contain information for both the dependent variable and the independent variable/es.

### 3.1.2 Research model and hypothesis development of Study 1

In employing initially "Price" (rental price per night in euros) as the dependent variable, the model did not pass the White's heteroscedasticity test for every statistical significance level. For that reason, the dependent variable that the model was transformed to "Log (Price)", and our model takes a semi-logarithmic form. Following the theory (and given the availability of required data), the independent variables are property attributes, accommodation amenities, location characteristics (i.e. distance from key location hubs), neighborhood qualities, contract rules, host attributes and reputation and trust attributes.

As property attributes we used the size of the accommodation, measured by the number of people that can be hosted as guests, the number of baths and the number of bedrooms, as well as the property type (if the accommodation on offer is an entire house or in a private room of the house). The variable *Number of beds* was not included in the model due to its strong correlation with the variable *Number of bedrooms*. The amenities of the listings that are examined are the availability of air-conditioning, cable TV and breakfast, whether the property is family friendly, and if smoking is allowed into the property (all dummy variables). As location variables we use the distance of the listing (in meters) from the center of Athens (Syntagma Square) and from the nearest metro station. Due to data availability, we employ only one variable that proxies the neighborhood quality, which is the population density of the neighborhood in which the property is located. The contract rules that have been examined are: the amount of the cleaning fee (in euros), the minimum period of stay (in nights), if a 24 hour check-in is offered (dummy variable) and if the listing is instantly bookable (dummy variable). The host attributes that we examine are the experience of hosts (in days) and if the host is a company or business (dummy variable). Finally, as proxies for reputation and trust we used the variables "Number of reviews" and the "Average rating score" for the listing and if the host has a "Verified ID" (dummy variable). Table 2 below presents all of the variables used.

Table 2: Description of variables of Study 1

| Variable | Description |
|---|---|
| Price (dependent variable) | Price per night (in euros) (log transformed) |
| ***Property attributes*** | |
| Guests | Number of people that can be hosted as guests |
| Bathrooms | Number of bathrooms |
| Bedrooms | Number of bedrooms |
| Entire home [a] | If the accommodation is an entire home |
| ***Accommodation amenities*** | |
| Air-conditioning [a] | If air-condition is available |
| Breakfast [a] | If breakfast is offered |
| Family-friendly [a] | If the accommodation is family friendly |
| Cable TV [a] | If cable TV is available |
| Smoking [a] | If smoking is allowed |
| ***Location (distances)*** | |
| City center | Euclidian distance to city center – Syntagma Square (m) |
| Metro | Euclidian distance to the nearest metro station (m) |
| ***Neighborhood qualities*** | |
| Density | Density of residents in neighborhood (residents/km$^2$ per neighborhood) |
| ***"Contract" terms (rules)*** | |
| Cleaning fee | Amount of cleaning fee (in euros) |
| Minimum nights | Minimum nights guest is allowed to stay |
| 24 hour check-in [a] | If guest is able to check-in 24hr per day |
| Instant booking [a] | If host does not need to confirm the booking |
| ***Host attributes*** | |
| Membership [b] | Experience in Airbnb (in days) |
| Company [a] | If host is a company or business |
| ***Reputation & trust attributes*** | |
| Number of reviews | Number of reviews of the listing |
| Review score | Average score rating of the listing |
| Verified ID [a] | If host's online ID is verified |

[a] Indicates a dummy variable (yes=1, no=0).
"Entire home": 1 if it is an entire house, 0 if it is a private room.
"Air conditioning": 1 if it is available, 0 otherwise.

"Breakfast": 1 if it is offered, 0 otherwise.
"Family-friendly": 1 it is family friendly, 0 otherwise.
"Cable TV": 1 if it is available, 0 otherwise.
"Smoking": 1 if it is allowed in the property, 0 otherwise.
"24 hour check-in": 1 if it is available, 0 otherwise.
"Instant booking": 1 if host does not need to confirm the booking, 0 otherwise.
"Company": 1 if the host is a company or business, 0 otherwise .

[b] The difference in days between the date that a host became member of Airbnb and the date that the observations was collected (9/5/2017).

The hypotheses that Study 1 examined are mostly based on the literature. The ones introduced by this study are H1e and H1r. The hypotheses that are of particular interest are H1s, H1t and H1u.

In accordance to the relevant literature (e.g. Wang and Nicolau 2017, Zhang et al 2017, Ert et al 2016, Gibbs et al 2018, Teubner et al 2017, Magno et al 2017), we assume that the size of the accommodation is associated with price positively. Thus:

H1a: The number of people that can be hosted as guests affect the price positively.

H1b: The number of bathrooms affect the price positively.

H1c: The number of bedrooms affect the price positively.

Wang and Nicolau (2017), Magno et al (2017), Ert et al (2016), Gibbs et al (2017) and Teubner et al (2017) have found that the entire house is related with a higher price. We support that if the use of the accommodation is in the entire house instead of in a private room, the rental prices get increased. So:

H1d: If the accommodation is an entire home, the effect on price is positive.

We consider that the more facilities offered, the higher are the prices. So, the first hypothesis will be:

H1e: If there is an air–conditioning available, the effect on price is positive.

Wang and Nicolau (2017) found that offering a breakfast affects the price negatively. However, for Dogru and Pekin (2017) the amenity of free breakfast increases the rental price. The hypothesis of this study is:

H1f: If breakfast is supplied, the effect on price is positive.

The same authors found that if the accommodation is family-friendly then the rental price increases. Thus,

H1g: If the accommodation is family friendly, the effect on price is positive.

As we discussed, the more amenities offered, the higher are the prices. This means that:

H1h: If cable–TV is offered, the effect on price is positive.

The allowance of smoking into the accommodation is associated with lower prices, according to Wang and Nicolau (2017). On these gronds, we assume that:

H1i: The allowance of smoking affects the price negatively.

Previous studies (Zhang et al 2017, Teubner et al 2017, Dogru and Pekin 2017, Gibs et al 2017, Li et al 2016) made clear that distance of property from location hubs decreases its rental price, therefore locational variables are expected to have a negative sign. As such we argue:

H1j: The distance of the accommodation to the city center affects the price negatively.

H1k: The distance of the accommodation to the nearest metro station, affects the price negatively.

In turn, the higher the population density (and arguably the attractiveness of the area to the population), the higher are the prices in that neighborhood. That means that:

H1l: The neighborhood population density affects the price positively.

Dogru and Pekin (2017) showed that the cleaning fee is associated with higher prices. Although Lee et al (2015) showed that the variable "minimum stay" affects the rental price and has a negative coefficient, Teubner et al (2017) found no significance. Teubner et al (2017) also did not find any significance on the variable "Check in/out comfort". Both Wang and Nicolau (2017) and Gibs et al (2018) found a negative coefficient on the variable "instant booking" (i.e. the host does not need to confirm the reservation). For exploring the findings of the literature, the hypotheses about the characteristics "Rules" are the following:

H1m: Cleaning fee affects price positively.

H1n: The number of minimum nights affects the price negatively.

H1o: 24 hour check-in affects the price positively.

H1p: If the listing is instantly bookable, the effect on price is negative.

With regard to the attributes "Host attributes and experience", a variable that is expected to have a positive effect on price is host experience (that is, since when a host owns at least one Airbnb listing) (Teubner 2017, Magno et al 2017).

H1q: Membership affects the price positively.

To our knowledge, there is no study that has examined the effect on price if the host is a company or business. We assume that companies generally have higher fixed costs in comparison to individuals and as a result they charge more in order to cover this kind of expenses. For that reason:

H1r: If the host is company or business, the effect on price is positive.

Although Airbnb asserts that the number of reviews has a positive impact on price (Hill 2015), Zhang et al (2017), Gibs et al (2017), Teubner et al (2017), Magno et al (2017) find this variable to have a negative coefficient. Likewise, Wang and Nicolau (2017) support that the number of reviews per year also affect the price negatively. Ert et al (2016) found no significance in the number of reviews, and also found the same result about the average customer rating. On these grounds we assert:

H1s: The number of reviews affect the price negatively.

However, most of the literature agrees that the higher the average customer rating, the higher is the price (Gibbs et al 2017, Teubner et al 2017, Wang and Nicolau 2017). As mentioned above (section 2.3), Gutt and Herrmann (2015) showed that if the average rating score is shown this leads to an increase in price by 2.69 euros. In addition, having a verified ID might be associated with a higher rental price (Wang and Nicolau 2017), but other researchers (Teubner et al 2017) argue for the opposite. The hypotheses we postulate are:

H1t: The score of reviews affect the price positively.

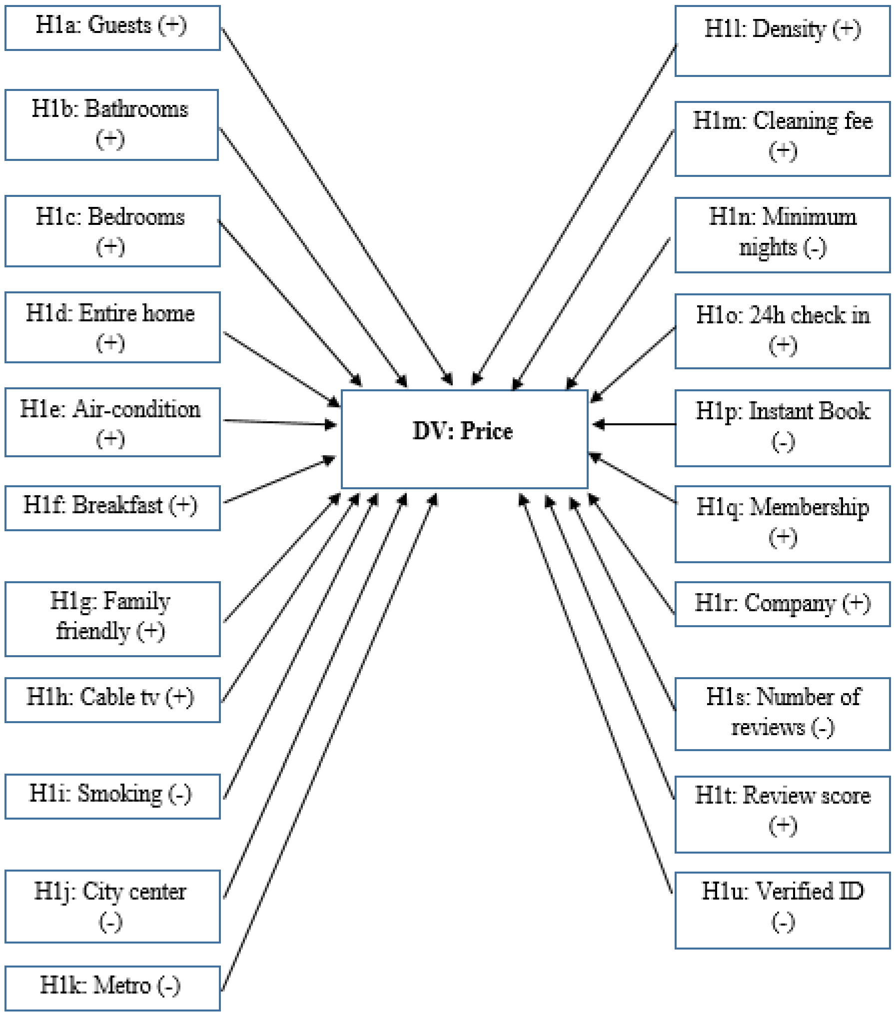
H1u: If host has a verified ID, it affects the price negatively.

Thus, based on the research hypotheses of Study 1, we can express our model as follows:

Log (price) i = $c_0$ + $c_1$ Guests i + $c_2$ Baths i + $c_3$ Bedrooms i + $c_4$ Entire _ home i + $c_5$ Air _ conditioning i + $c_6$ Breakfast i + $c_7$ Family_Friendly i + $c_8$ Cable tv i + $c_9$ Smoking i + $c_{10}$ City_ Center i + $c_{11}$ Metro i + $c_{12}$ Density i + $c_{13}$ Cleaning_ fee i + $c_{14}$ Minimum_ nights i + $c_{15}$ 24h_ check_ in i + $c_{16}$ Instant_ booking i + $c_{17}$ Membership i + $c_{18}$ Company i + $c_{19}$ Number_ of_ reviews i + $c_{20}$ Review_ score i + $c_{21}$ Rev i + $c_{22}$ Verified_ ID i + εi

Where $c_i$ are the coefficients and $\varepsilon_i$ are the residuals.

Figure 3: Research hypotheses of Study 1.




## 3.2 Methodology of Study 2

This study examines what determine the hosts' trust. Specifically, we explore what attributes determine the trust host place in the prospective guests. For this purpose, six Logit models (LOGIT1, LOGIT2, LOGIT3, LOGIT4, LOGIT5, LOGIT6) are developed. The sample examined is the same as in Study 1 (i.e. the 311 Airbnb listings). The diagnostic test of normality (using Jargue Bera's test) is applied and presented in the Appendix.

### 3.2.1 The logistic regression model (Logit)

According to Halkos (2011), the logistic regression model (Logit) guarantees that the estimated probabilities are ranged between 0 and 1 and are non – linear correlated with the independent variables. The Logit model is based on the Log – transformation of the odds ratio. The dependent variable is a binary variable (Y) which takes the values of 0 and 1 with probabilities Θ and Θ – 1. That kind of variable follows a simple distinct distributions of the probabilities, defines as:

$$\Pr(Y_i, \Theta_i) = \Theta_j^{Y_i} (1 - \Theta_i)^{1 - Y_i}$$

Given the mutually exclusive $Y_1, Y_2, \ldots Y_n$, the probability function constitutes the product of the marginal allocations of $Y_i$. The coefficients $\beta_j$ of the model measure the relation between the independent variables and the dependent variable including the odds ratio.

$$\text{Odds}(E \mid X_1, X_2, \ldots, X_n) = \Pr_i(E) / 1 - \Pr_i(E)$$

The logistic regression maximizes the probability for an event to happen.

$$\text{Ln}(P_i / 1 - P_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_\kappa X_\kappa$$

The equation above approaches the odds ratio like a linear equation of the independent variables and is equivalent to a multiple regression model with the odds ratio to be the dependent variable. The form of the model is a modification of the probability Pr(Y=1) which is defined as the physical logarithm of odds of the event E(Y=1).

This method is more preferred than the multiple regression analysis, since the dependent variable is a binary, discontinuous variable.

### 3.2.2 Research model and hypotheses development of Study 2

Since the aim of the Study 2 is to explore the determinants of trust of hosts in potential guests, we had to quantify this kind of trust. The system enables hosts to ask from prospective guests their profile picture and/or to verify their phone in order to confirm the reservation (Airbnb.com 2018). We argue that if a host requires both pieces of information (i.e. guest's profile picture and phone verification), this can be seen as an indicator of low trust towards guests. In contrast, we assert that a host trusts prospective guest in the case of not requiring guest's profile picture and phone verification.

On the basis of the above, the dependent variable we develop is a binary variable (and so our model is logit), that takes the value of 1 if a host does not require both guest's profile picture and guest's phone verification, and 0 if they require either guest's profile picture or their phone verification there is no trust from the host toward the guest, so the variable "Trust" takes the amount of 0.

The independent variables that we examine are the gender of hosts, the number of languages that they speak, if the hosts have a verified ID, their experience with Airbnb (in days), the average rating score of the listing concerned and the number of reviews that the listing has. The description of the variables is presented in the following table (Table 3).

Table 3: Description of variables of Study 2.

| **Variable** | **Description** |
|---|---|
| Trust [a] | If guest's profile picture is not required<br>If guest's phone verification is not required |
| Host gender [a] | Host's gender |
| Number of languages | The number of languages that the host speaks |
| Superhost [a] | If host has a superhost status |
| Verified ID [a] | If host's online ID is verified |
| Membership [b] | Host's experience in Airbnb (in days) |
| Review score | Average score rating of host's listing |
| Number of reviews | Number of reviews of host's listing |

[a] Indicates a binary variable (yes=1, no=0).
"Trust": 1 if both guest's profile picture and phone verification are not required by the host, 0 otherwise.
"Host gender": 1 if the host is a man, 0 if the host is a woman.
"Superhost": 1 if the host has a Superhost status, 0 otherwise.
"Verified ID": 1 if the host has a verified ID, 0 otherwise.

[b] The difference in days between the date that hosts became members of Airbnb and the date that the observations was collected (9/5/2017).

Given that a study like this has not been undertaken before, our hypotheses are based on the findings of the general literature and on logical assumptions.

Various pieces of literature (e.g. Alessina and Ferrara 2002) has shown that females are less likely to trust others. For that reason we hypothesize that if the hosts are men, they are more likely to trust their guests in comparison with women.
H2a: If the host is a man, he is more likely to trust the guests.

The number of languages someone speaks indicate openness, tolerance and a degree of cosmopolitanism. On these grounds we argue:
H2b: The more languages the host speaks, he/she is more likely to trust the guests.

To become a superhost, a host has to fulfill the following requirements: to have completed at least 10 trips, maintained a 50% review rate or higher, maintained a 90% response rate or higher, have 0 cancellations and received a 5-star review at least 80% of the time (Airbnb.com 2018). We reckon that such a superhost is quite keen on Airbnb sharing economy model and this should be associated with high levels of trust towards peers and prospective guests. Thus:

H2c: Being a superhost, a host is more likely to trust prospective guests.

As regards the verified ID, we argue that a host seeks such a qualification[3] because they want to be trusted by the platform, the peers and the guests. For that reason, we assert that such a person might be more reserved and sceptic towards strangers. Therefore:
H2d: Having a verified ID, the host is less likely to trust the guests.

Turning to host experience in Airbnb, we believe that the more experienced the host is the more familiar they get with the Airbnb business model and so more trustful they become to both the system and to prospective guests. On these grounds:
H2e: The more experienced the host is, the more is likely to trust the guests.

So is the case for the review score and the number of reviews. We support that the higher a review score and the number of review a listing has, the host is more comfortable and more experienced with the concept of the sharing economy, and therefore they are likely to trust potential guests. So:
H2f: The higher a review score a listing has, the host is more likely to trust the guests.
H2g: The more reviews a listing has, the host is more likely to trust the guests .

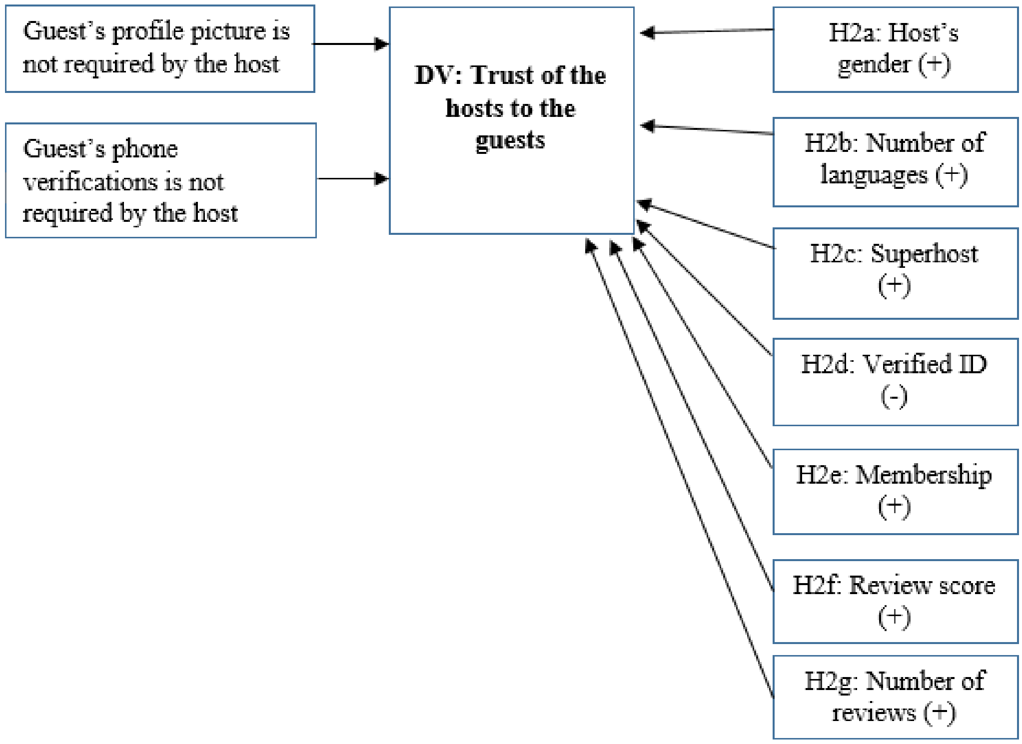
Based on the hypotheses development above, we can express our model as follows:

$$\text{Logit (Trust) } i = c_0 + c_1 \text{ Host\_gender } i + c_2 \text{ Number\_of\_languages} + c_3 \text{ Superhost } i - c_4 \text{ Verified\_ID} + c_5 \text{ Review\_ score } i + c_6 \text{ Number\_of\_reviews} + \varepsilon\, i$$

Where $c_i$ are the coefficients and $\varepsilon_i$ are the residuals.

[3] Airbnb users can earn a "Verified ID" badge on their profile by providing their online identity via existing Airbnb reviews, LinkedIn, or Facebook and matching it to offline ID documentation, such as confirming personal information or scanning a photo ID (Airbnb.com 2018).

Figure 4: Research hypotheses of Study 2.




To conclude, for the exploration of the explanatory variables of the rental price of the 311 housing listings, we perform OLS models (hedonic pricing – semi-logarithmic form). For the exploration of host's trust in guests, we use LOGIT models, in order to examine the impact of some characteristics of the hosts and the listings. The selection of the variables have been mostly based in the literature. However, we also introduce some parameters in order to enrich the literature.

# Chapter 4: Analysis

This chapter presents the analyses of both studies; in particular, section 4.1 provides the analysis of Study 1 and 4.2 the analysis of Study 2. In each section we describe the results of the descriptive statistics and the econometric analyses of Study 1 and Study 2 respectively. The descriptive statistics were acquired by Microsoft Excel 2013 and the econometric analyses with Eviews 9 Student version.

## 4.1 Analysis of Study 1

Study 1 is designed to estimate the factors that affect the market rental prices of Airbnb listings. In total, 311 houses which are located in the center of Athens, Greece, are examined. For the rental price valuation, the hedonic pricing method was used, examining a number of OLS models, of which three are presented here. As discussed, the dependent variable of the models is the log transformed rental price per night (in euros). However, a reported limitation of the hedonic pricing method is that it offers limited theoretical guidelines for selecting explanatory variables (Anderson 2000). Theoretically, the independent variables are the constructional (or property) features, the neighborhood features, the location attributes, the characteristics of the contract and the time the rent or value is observed. The selection of the independent variables in our model was mostly based on similar works on Airbnb (i.e. Gibs et al 2018, Wang and Nicolau 2017, Teubner et al 2017, Ert et al 2016, Zhang et al 2017, Magno et al 2017, Dogru and Pekin 2017, Lee et al 2015).

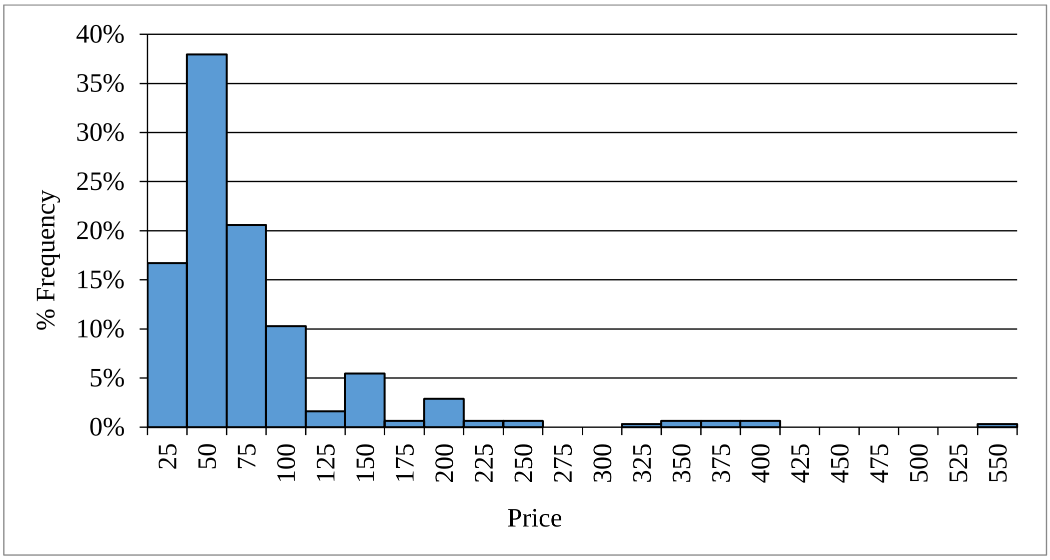
### 4.1.1 Descriptive statistics

This section presents the descriptive statistics of the variables used. First, we present the variables of interest (trust and reputation) and next the rest. Thus, we start with the variables “Price”, “Number of reviews”, “Review score” and “Verified ID” presenting the average values, the standard deviations, the means and the minimum and maximum amounts of these variables. The descriptive statistics of the rest of the independent variables used follows.

Although the dependent variable of our models is the “Log (Price)”, following standard practice we present the characteristics of the variable “Price” (see Figure 5 and Table 4). As it is shown in Figure 5, the majority of houses is priced between 25 and 75 euros per night, whereas the average rental price of Airbnb houses (entire homes and private rooms) is 69,82 euros per night.

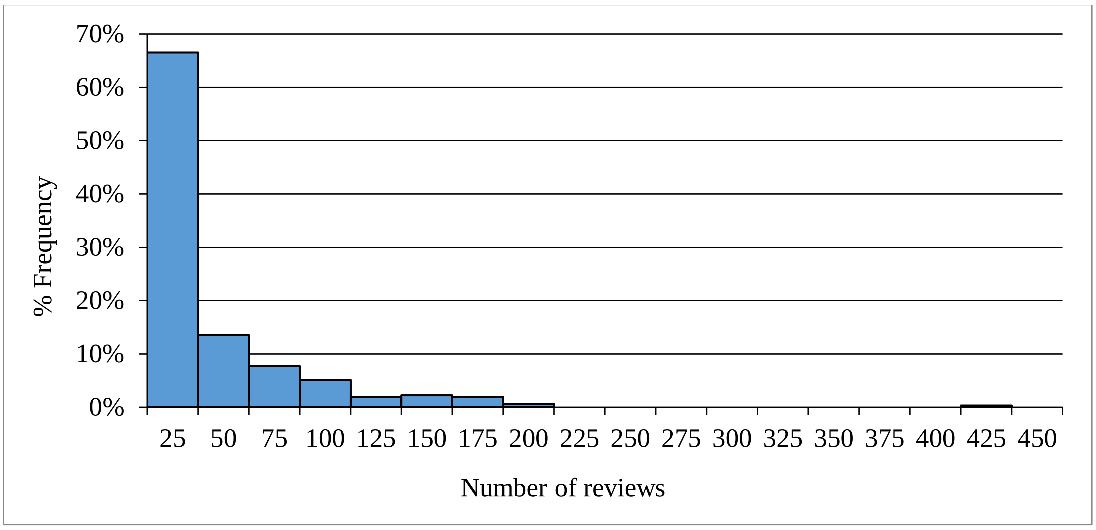
The standard deviation of prices is 68,706 and the mean is 50 euros per night. The minimum price that is observed is 9 euros per night and the maximum is 526.

Figure 5: Distribution of the variable "Price" (in Euros per night - Percent Histogram).



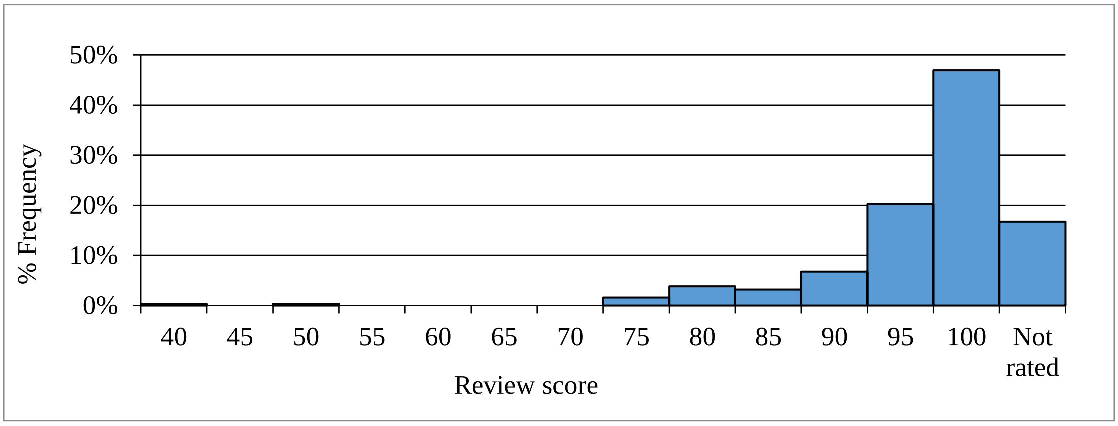

The factor that Study 1 focuses on, is reputation and trust attributes, as measured by the "Number of reviews", "Review score", and "Verified ID". Most of the amounts of the "Number of reviews", are between 0 and 25 (Figure 6). It is shown in Table 4 that the average number of reviews is 29,21. That means that the average listing has 29,21 reviews. It must be mentioned that 16,73% (52 out of 311) of the listings have not been rated, and that is the reason why the model's sample is reduced to 259 observations after adjustments.

Figure 6: Distribution of “Number of reviews” (Percentage Histogram).



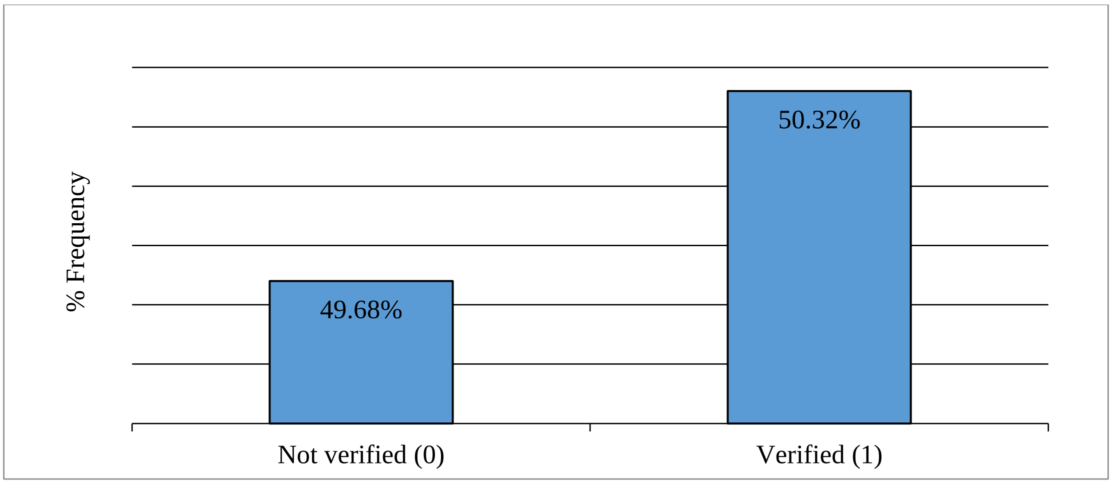

Most of the review scores of the listings are between 90 and 100 (Figure 7). The average review score is 94,193 (i.e the average listing has been rated with 94,193 out of 100). The standard deviation of this variable is 7,61 and the mean is 96.

Figure 7: Distribution of the variable “Review score” (Percentage Histogram).




The 50,32% of hosts have a verified ID and the median of this variable is 1, so our population is nearly distributed into two halves (i.e 50,32% of hosts have a verified ID, and the rest 49,68% have not).

Figure 8: Distribution of the variable “Verified ID” (Percentage Histogram).




The descriptive statistics of the rest variables that are used in the research model of Study 1, are outlined in the following table (Table 4).

It is interesting to note that the average number of guests is 4,07. That means that the Airbnb houses which are located in the center of Athens are capable of hosting 4 people approximately. As was mentioned above, 75,72% of our listings are entire homes and the rest 24,28% are private rooms. Moreover, the 3,53% of the hosts are companies or businesses. The average membership of hosts in Airbnb (experience) is 960,93 days. As can be seen, the average house listing has 1,36 bathrooms, 1,63 bedrooms, it has an air-condition, it is family-friendly, but it does not offer breakfast or cable TV, and smoking is not allowed. Most of the houses do not offer 24-hour check-in or instant booking. On average these listings are close to the city center (at a distance of about 1700m) and quite close to a metro station (about 500m).

Table 4: Descriptive statistics of Study 1.

| Variable | Average | St. dev | Median | Min | Max |
|---|---|---|---|---|---|
| Price | 69,82 | 68,706 | 50 | 9 | 526 |
| ***Property attributes*** | | | | | |
| Guests | 4,0675 | 2,3799 | 4 | 1 | 16 |
| Bathrooms | 1,3601 | 0,6725 | 1 | 0,5 | 5,5 |
| Bedrooms | 1,6334 | 0,966 | 1 | 0 | 7 |
| Entire home | 0,7572 | 0,4287 | 1 | 0 | 1 |
| ***Accommodation amenities*** | | | | | |
| Air-conditioning | 0,7184 | 0,4497 | 1 | 0 | 1 |
| Breakfast | 0,2297 | 0,4206 | 0 | 0 | 1 |
| Family-friendly | 0,7508 | 0,4325 | 1 | 0 | 1 |
| Cable TV | 0,1197 | 0,3246 | 0 | 0 | 1 |
| Smoking | 0,3818 | 0,4861 | 0 | 0 | 1 |
| ***Location (distances)*** | | | | | |
| City center | 1727,657 | 963,1929 | 1615,648 | 43,0961 | 5694,45 |

| | | | | | |
|---|---|---|---|---|---|
| Metro | 556,7031 | 309,2394 | 492,6047 | 21,1962 | 1566,273 |
| ***Neighborhood qualities*** | | | | | |
| Density | 18429,44 | 7647,912 | 18670,78 | 7827,52 | 31689,91 |
| ***"Contract" terms (rules)*** | | | | | |
| Cleaning fee | 17,881 | 16,3956 | 15 | 0 | 80 |
| Minimum nights | 2,0514 | 2,4919 | 2 | 1 | 28 |
| 24 hour check-in | 0,3268 | 0,469 | 0 | 0 | 1 |
| Instant booking | 0,4612 | 0,4984 | 0 | 0 | 1 |
| ***Host attributes*** | | | | | |
| Membership | 960,9355 | 586,4922 | 810 | 7 | 2274 |
| Company | 0,0353 | 0,1847 | 0 | 0 | 1 |
| ***Reputation & trust attributes*** | | | | | |
| Number of reviews | 29,2186 | 46,2651 | 8 | 0 | 425 |
| Review score | 94,193 | 7,6168 | 96 | 40 | 100 |
| Rev | 3267,722 | 4528,184 | 1302 | 0 | 40375 |
| Verified ID | 0,5032 | 0,4999 | 1 | 0 | 1 |

### 4.1.2 Hedonic price models

The OLS1 model shows all of the variables that we used. The OLS2 model uses all of the variables except from the variable "Instant booking". The OLS3 model do not analyze the variables "24h check-in", "Instant booking and "Density". The analysis in the OLS4 model is limited to the variables that are statistically significant for $\alpha = 0{,}01$, $\alpha = 0{,}05$ and $\alpha = 0{,}10$ in the previous models, and the variables that Study 1 is focused on (reputation and trust attributes). The OLS4 model has the lowest value of AIC (AIC = 0.831169) in comparison with the rest of the models. For that reason, only the results of the OLS4 model will be discussed, since this represents the best model.

The adjusted $R^2$ value indicates that the OLS4 model explains by 74.782% of the variance in Airbnb listing prices. The OLS4 model is statistically significant for any $\alpha$ ($\alpha = 0.01$, $\alpha = 0.05$, $\alpha = 0.10$) by whole, since the F – statistic equals to 48.261 and the Prob. (F – statistic) equals to 0.000. Table 5 also includes the percentage change in accommodation price associated with the attributes that were found to be statistically significant. When assessing the influence of a dummy coded variable on a logarithmically transformed dependent variable, one must transform the coefficient by ($e^{\beta} - 1$), with $\beta$ representing the coefficient and e representing the base of the natural logarithm (Halvorsen & Palmquist 1980). For example, a hypothetical coefficient of 0.30 would signify that this attribute results in a 34,98% increase [exp. (0.30) – 1] in the price of an Airbnb listing, if the rest key variables remain stable (ceteris paribus). In all of the interpretations that follow, when we describe a result of the percentage change of an attribute in the rental price of a listing, we assume that the rest of the independent variables remain stable (ceteris paribus).

All the property attributes have positive sign, meaning that their existence is associated with higher rental prices. In OLS4, it is observed that each additional guest increases the rental price by 8,4961%. Similarly, each additional bathroom increases the listing price by 33.1705%. If the use of the accommodation is in the entire home, instead of in a private room, the price is 30.7125% higher. Thus, the larger the accommodation, the higher the price.

In the case of offered amenities like air-conditioning and cable TV, prices will be increased by 25.663% and 14.286% respectively. If the accommodation is family-friendly, the listing price per night is increased by 11.804%. However, when smoking is allowed in the accommodation the rental price per night gets reduced by 14.286%.

Turing to location attributes, both distance to the city center (Syntagma Square) and distance to the nearest metro station have negative signs, which means that the closer the accommodation is to these points the higher are the rental prices. We found that if an accommodation is located 1 meter further from the city center, the price gets reduced by 0,0188% and if the house is located 1 meter further from the nearest metro station, the price gets reduced by 0,0175%.

The cleaning fee is statistically significant for $\alpha = 0,01$. When the cleaning fee is increased by 1 euro, the rental price per night gets increased by 0,5347%. The minimum stay in nights is also statistically significant, but for $\alpha = 0,10$. When the minimum stay gets increased by 1 night, the charge gets reduced by 3,583%.

The host attributes that Study 1 investigates, is the duration of membership with Airbnb (experience) and if the host is a company or business instead of being an individual. Both variables are statistically significant for $\alpha = 0,05$. If the host gets more experienced by 1 day, the rental price gets increased by 0,0082%. If the host is a company or business, the charge is observed to be increased by 34.54%.

The characteristics that Study 1 is focused on, are host reputation and trust attributes. Specifically, it examines the variables “Reviews score”, “Number of reviews”, and “Verified ID”. It is shown in Table 4 that the variable “Review score” (i.e. the average star rating of the listing) has no significance (for every statistical significance level), so it does not affect the price. The same result also occurs with the variable “Number of reviews”. “Verified ID” has a coefficient equal to – 0,0911 and is statistically significant for $\alpha = 0,10$. This means that when a host has a verified ID, the price gets reduced by 8,710%.

Table 5: Hedonic Price Models.

| DV: Log (Price) | | | |
|---|---|---|---|
| **Variable** | **OLS1** | **OLS2** | **OLS3** |
| Constant | 3.039281 (9.625) *** | 3.032304 (9.837) *** | 2.977823 ( 9.699) *** |
| ***Property attributes*** | | | |
| Guests | 0.076530 (4.154) *** | 0.076426 (4.163) *** | 0.074868 ( 4.074) *** |
| Bathrooms | 0.266884 (5.617) *** | 0.267763 ( 5.735) *** | 0.274558 ( 5.886) *** |
| Bedrooms | 0.036659 (0.831) | 0.036673 ( 0.833) | 0.029276 ( 0.667) |
| Entire home | 0.270151 (4.132) *** | 0.269420 ( 4.153) *** | 0.275076 ( 4.288) *** |
| ***Accommodation Amenities*** | | | |
| Air-conditioning | 0.240699 (4.418) *** | 0.240391 (4.427) *** | 0.242694 ( 4.460) *** |
| Breakfast | 0.089003 (1.613) + | 0.088346 (1.615) + | 0.084006 ( 1.533) + |
| Cable TV | 0.137645 (1.927) * | 0.137389 (1.929) * | 0.106063 ( 1.791) * |
| Family- friendly | 0.105854 (1.786) * | 0.105547 (1.787) * | 0.123463 ( 1.741) * |
| Smoking | -0.15220 (-2.942)*** | -0.15381 (-2.995)*** | -0.142848 (-2.837)*** |
| ***Location (distances)*** | | | |
| City center | -0.00017 (-5.614)*** | -0.000177 (-5.625) *** | -0.000191 (-6.252)*** |
| Metro | -0.000126 (-1.439) | -0.000126 (-1.439) | -0.000180 ( -2.272)** |
| ***Neighborhood qualities*** | | | |
| Density | -7.14E-06 (-1.364) | -7.15E-06 (-1.370) | |
| ***"Contract" terms (rules)*** | | | |
| Cleaning fee | 0.004988 (2.736) *** | 0.004997 (2.750) *** | 0.005031 (2.793) *** |
| Minimum nights | -0.034348 (-1.810) * | -0.034180 (-1.811) * | -0.033944 (-1.811)* |
| 24 hour check-in | -0.062200 (-1.221) | -0.06158 ( -1.220) | |
| Instant booking | -0.005178 (-0.106) | | |
| ***Host attributes*** | | | |
| Membership | 9.15E-05 (2.210) ** | 9.20E-05 (2.242) ** | 8.66E-05 (2.114) ** |
| Company | 0.303257 (1.936) * | 0.301699 (1.938) * | 0.302366 (1.952) * |
| ***Reputation & trust attributes*** | | | |
| Review score | 0.001305 (0.406) | 0.001344 ( 0.422) | 0.001379 (0.432) |
| Number of reviews | -0.000125 (-0.245) | -0.000130 (-0.257) | -0.000128 (-0.253) |
| Verified ID | -0.080771 (-1.689) * | -0.081166 (-1.706) * | -0.079144 ( -1.662) * |
| | | | |
| Adj. $R^2$ | 74,874% | 74,979% | 74,85% |
| AIC | 0.845439 | 0.837675 | 0.835456 |
| F – value | 37.18500 | 39.20863 | 43.17549 |
| Prob. (F – value) | 0.000000 | 0.000000 | 0.000000 |
| N | 256 | 256 | 256 |

***p<α=0,01, **p<α=0,05,*p<α=0,10, + likely to be statistically significant for a=0,10. (t – statistics). [percentage change in price].

Table 5 (Cont.): Hedonic Price Models.

| DV: Log (Price) | |
|---|---|
| **Variable** | **OLS4** |
| Constant | 2.998220 (9.765) *** |
| ***Property attributes*** | |
| Guests | 0.081544 (5.800) *** [8,4961%] |
| Bathrooms | 0.286460 (6.485) *** [33,1705%] |
| Bedrooms | |
| Entire home | 0.267830 (4.180) *** [30,7125%] |
| ***Accommodation Amenities*** | |
| Air-conditioning | 0.228439 (4.250) *** [25,6637%] |
| Breakfast | |
| Family friendly | 0.133536 (1.888) * [14,2862%] |
| Cable TV | 0.111585 (1.885) * [11,8049%] |
| Smoking | -0.142240 (-2.824) ***[14,2862%] |
| ***Location (distances)*** | |
| City center | -0.000188 (-6.158) *** [-0,0188%] |
| Metro | -0.000175 (-2.206) ** [-0,0175%] |
| ***Neighborhood qualities*** | |
| Density | |
| ***"Contract" terms (rules)*** | |
| Cleaning fee | 0.005333 (3.018) *** [0,5347%] |
| Minimum nights | -0.036495 (-1.962) * [-3,5837%] |
| 24 hour check-in | |
| Instant booking | |
| ***Host attributes*** | |
| Membership | 8.20E-05 (2.003) ** [0,0082%] |
| Company | 0.296698 (1.927) * [34,5409%] |
| ***Reputation & trust attributes*** | |
| Review score | 0.001555 (0.488) |
| Number of reviews | -0.000203 (-0.405) |
| Verified ID | -0.085086 (-1.795) * [-8,1567%] |
| | |
| Adj. $R^2$ | 74,782% |
| AIC | 0.831169 |
| F – value | 48.26168 |
| Prob. (F – value) | 0.000000 |
| N | 256 |

***p<α=0,01, **p<α=0,05,*p<α=0,10, + likely to be statistically significant for a=0,10. (t – statistics). [percentage change in price].

According to OLS1, OLS2, and OLS3 models, the variables "Bedrooms", "Breakfast", "Density", "24hr check-in", "Instant booking", "Review score" and "Number of reviews" have no influence on the rental price per night. Thus, the hypotheses that Study 1 rejects are: H1c, H1f, H1l, H1o, H1p, H1s and H1t and those which it accepts are H1a, H1b, H1d, H1e, H1g, H1h, H1i, H1j, H1k, H1m, H1n, H1q H1r and H1u.

All of the three presented models have been checked for heteroscedasticity (White's test), multicollinearity (Variance Inflator Factors) and regularity normality (Jargue Bera's test) (these tests are available in the Appendix). We found that none of our models has the problems of heteroscedasticity and multicollinearity. Unfortunately, the residuals do not follow normal distribution in all of the five OLS models.

## 4.2 Analysis of Study 2

Study 2 assesses the attributes that affect the trust of hosts in their prospective guests. The analysis is performed on the same sample (311 listings) as in Study 1 appling six LOGIT models (Logistic regression) with the quantified independent variable "Trust", as we described in the section 3.3.2. The independent variables that we examine are key available characteristics of the hosts.

### 4.2.1 Descriptive statistics

As it is shown in Figure 9, the majority of values of the variable "Trust" is 1, whereas the average of "Trust" is 0,9433. It seems that the 283 out of 300 of the hosts who own or manage the listings, trust the prospective guests. This means that the 94,33% of host do not require both guest's profile picture and their phone verification. This can be interpreted as: 94,33% of hosts trust the prospective guests. The standard deviation of "Trust" is 0,2312.

Figure 9: Distribution of "Trust" (Percentage Histogram).

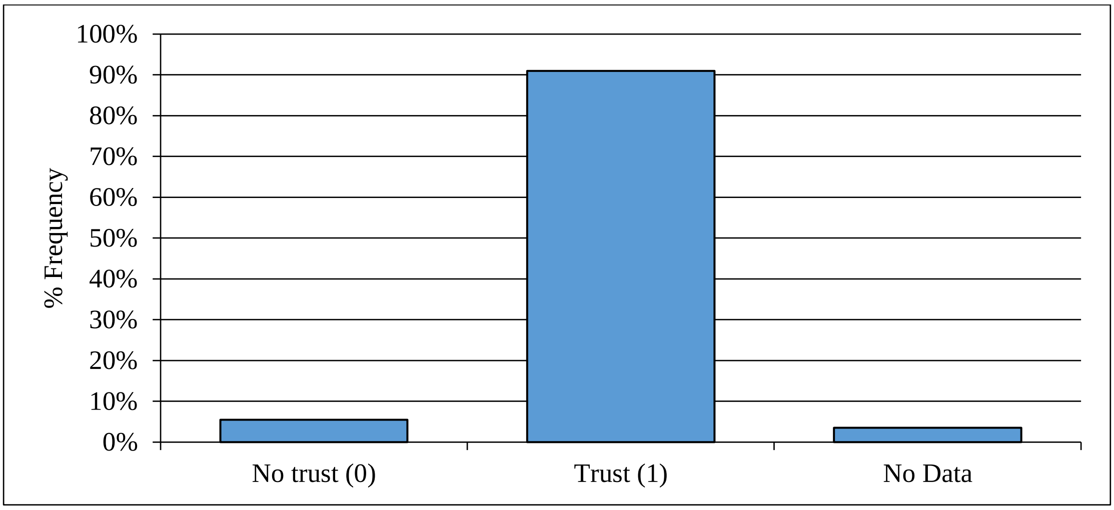


Table 6 presents the descriptives of the other variables used. As it is shown, 45,64% of the hosts are men and the rest 54,36% are women. The average host speaks 2,08 languages and 23,22% of them are Superhosts. The variables "Verified ID", "Membership", "Review score" and "Number of reviews" have also been examined. We see that 50,32% of hosts have a verified ID, the average host has experience of 960,93 days with Airbnb, the average listing has been rated with 94,193 (out of 100) and has 29,21 number of reviews.

Table 6: Descriptive statistics of variables of Study 2.

| **Variable** | **Average** | **St. dev** | **Mean** | **Min** | **Max** |
|---|---|---|---|---|---|
| Trust | 0,94333 | 0,2312 | 1 | 0 | 1 |
| Host gender | 0,4564 | 0,498 | 0 | 0 | 1 |
| Number of languages | 2,0878 | 1,077 | 2 | 1 | 7 |
| Superhost | 0,2322 | 0,4222 | 0 | 0 | 1 |
| Verified ID | 0,5032 | 0,4999 | 1 | 0 | 1 |
| Membership | 960,935 | 586,492 | 810 | 7 | 2274 |
| Review score | 94,193 | 7,616 | 96 | 40 | 100 |
| Number of reviews | 29,21 | 46,265 | 8 | 0 | 425 |

### 4.2.2 Logit models

Study 2 has performed in total six LOGIT models. All these are presented in Table 7 that follows, so that the reader to have a better understanding of how the variables affect host trust towards prospective guests. The LOGIT1 model shows all of the variables that we use. LOGIT2 model analyses all of the variables that we used in the LOGIT1 model except for the variable "Number of languages". LOGIT3 shows all the variables except for the variable "Gender". In the LOGIT4 model we excluded the variables "Gender", "Number of languages" and "Review score". In LOGIT5 the variables that are excluded from the analysis are "Gender" and "Number of languages" and in LOGIT6 the variable "Review score" is excluded. In comparison to all of the LOGIT models, the LOGIT4 has the lowest value of AIC (AIC = 0,3118), and as such we deem it to be the best model of the six. For that reason, the results of the LOGIT4 model will only be discussed next.

LOGIT4 shows that statistically significant for statistical significance level ($\alpha$) equal to 0,01 is only the variable "Membership" (p=0,000). For $\alpha$=0,05, the variable "Number of reviews" is significant (p=0,0162), and the variable "Verified ID" is significant for $\alpha$=0,10 (p=0,0844). So, based on the LOGIT4 model these are the variables that determine the trust of hosts in guests, in the corresponding statistical significance levels. LOGIT4 is statistically significant as a whole for every $\alpha$ ($\alpha$ = 0,01, $\alpha$ = 0,05, $\alpha$ = 0,10), since the LR statistic equals to 41,58 and the Prob. (LR statistic) equals to 0,000.

For the aforementioned model we estimated the odd ratios[4] in order to acquire the probabilities of variables that affect the trust of the hosts in the prospective guests. The coefficient of the variable “Verified ID” is -1,2286 which implies that e-1,2286 = 0,2926 so the odds ratio of “Verified ID” is 0,2926 - 1 = -0,79735. This result means that if the host has a verified ID the probability of trusting a prospective guest gets reduced by 70,738%, if the rest of the factors of the model remain stable (ceteris paribus). The variable “Membership” has a coefficient of -0,00291, and the odds ratio equals to -0,002909. This means that as the experience of the host increases, the probability of trusting guests gets reduced by 0,2909% (ceteris paribus). it can be argued that the more experienced the host is, the more bad events he has lived through during his Airbnb membership. As a result, we hypothesize that the more experience the host has, the less likely he trusts potential guests. Similarly, the coefficient of “Number of reviews” is -0,01114. Thus, as the number of reviews of the host’s listing increases by one unit, the probability of trusting a guest gets reduced by 1,114% (ceteris paribus). A possible explanation of why high number of reviews might lead to lower levels of trust is because as the number of reviews increases a host might expect to get some “bad” (low-rated) reviews, and as a result they might be less likely to trust future guests.

Concluding this section let us discuss the results of all models and the general conclusion that can be drawn. Fist, the variable “Gender” does not seem to play any role in trust, since it remains statistically not significant. This indicates that there is no difference in the trust attitude between men and women. So is the case for the variable “Number of languages”, indicating that Greek hosts trust their guests in a similar way independent of the degree of their cosmopolitanism. The variable “Superhost” is positive and marginally statistically significant in 2 models, but significant in LOGIT2 for $\alpha$=0,10 (p=0,0901). The coefficient equals to 1,473 and the odds ratio is 3,3663. This means that if the host has a Superhost status, the probability of trusting a guest gets increased by 336,633% (ceteris paribus). Overall, Based on the models LOGIT2 and LOGIT4, we accept the hypotheses H2c, H2d, but we reject the hypotheses H2a, H2b, H2, H2f and H2g.

[4] Odd ratios are listed in the brackets [] in Table 6.

Table 7: Results of LOGIT models.

| **Variable** | **LOGIT1** | **LOGIT2** | **LOGIT3** |
|---|---|---|---|
| Constant | 14.806 (1.736) * | 16.522 (2.226) ** | 12.364 (1.529) + |
| Host gender | 0.025 (0.038) [0,02536] | -0.059 (-0.089) [-0,0574478] | |
| Number of languages | 0.372 (1.247) [0,4516139] | | 0.364 (1.182) [0,440314] |
| Superhost | 1.393 (1.59) + [3,0292248] | 1.473 (1.695)* [3,3663394] | 1.129 (1.418) [2,094876] |
| Verified ID | -1.564 (-2.07) ** [-0,7907562] | -1.607 (-2.124)** [-0,1484804] | -1.321 (-1.813)* [2,747298] |
| Membership | -0.003 (-3.941) *** [-0,0030723] | -0.0031 (-4.128)*** [-0,0030962] | -0.002 (-3.821)*** [-0,002923] |
| Review score | -0.080 (-0,958) [-0,0772215] | -0.087 (-1.210) [-0,0840257] | -0.057 (-0.713) [-0,055485] |
| Number of reviews | -0.0109 (-2.042)** [-0,0108458] | -0.011 (-2.221)** [-0,0113323] | -0.0099 (-1.957) * [-0,009869] |
| | | | |
| McFadden $R^2$ | 0.3644 | 0,3511 | 0.3398 |
| AIC | 0,3958 | 0,3723 | 0,3841 |
| LR statistic | 42.11 | 41.23 | 39,86 |
| Prob. (LR statistc) | 0,0000 | 0,0000 | 0,0000 |
| N (after adjustments) | 226 | 239 | 238 |

***p<α=0,01, **p<α=0,05,*p<α=0,10, + likely to be statistically significant for a=0,10. (z – Statistics). [Odds Ratio].

Table 7 (cont.): Results of LOGIT models.

| **Variable** | **LOGIT4** | **LOGIT5** | **LOGIT6** |
|---|---|---|---|
| Constant | 8.024 (5.575)*** | 14.5163 (2.0548)** | 7.0355 (4.7488) *** |
| Host gender | | | 0.2115 (0.3248) [0,235602] |
| Number of languages | | | 0.3680 (1.1884) [0,444945] |
| Superhost | 0.8002 (1.1266) [1,226186] | 1.219461 (1.5671) + [2,385363] | 0.8743 (1.1398) [1,397422] |
| Verified ID | -1.2286 (-1.7256)* [-0,707308] | -1.391201 (-1.9067) *** [-0,751224] | -1.4399 (-1.9516) * [-0,763062] |
| Membership | -0.00291(-4.1146)*** [-0,002909] | -0.002975 (-3.9958)*** [-0,002971] | -0.0028 (-4.0761)*** [-0,002891] |
| Review score | | -0.069197 (-0.9910) [-0,066857] | |
| Number of reviews | -0.0112 (-2.4048)** [-0,011144] | -0.010556 (-2.1745)** [-0,010500] | -0.0117 (-2.2627) ** [-0,011713] |
| | | | |
| McFadden $R^2$ | 0.3331 | 0,3284 | 0,3687 |
| AIC | 0.3118 | 0,3663 | 0,3377 |
| LR statistic | 41.58 | 39.09 | 44,69 |
| Prob. (LR statistic) | 0,0000 | 0,0000 | 0,0000 |
| N (after adjustments) | 299 | 251 | 268 |

***p<α=0,01, **p<α=0,05,*p<α=0,10, + likely to be statistically significant for a=0,10. (z – Statistics). [Odds Ratio]

# Chapter 5: Conclusions

The aim of this research was to explore the key determinants of the rental prices of Airbnb listings, placing particular emphasis on the role of hosts' reputation and trust towards guests. The Athens' house Airbnb market was used as a case study. This chapter discusses the results of the study, highlighting a number of conclusions drawn and pointing out directions where future work can follow.

Our first set of models (Study 1) was indented to assess the significance of reputation and trust attributes on (along with other attributes that affect) the rental price of Airbnb house listings in Athens. By applying a number of hedonic price models, the results show that only the variable "Verified ID" (i.e. if the host has his online ID verified on Airbnb) is significant, having a negative effect on price. Surprisingly, the average score rating and the number of reviews have no influence on the rental prices of Airbnb listings in Athens. The negative effect that the Verified ID has on price, implies that hosts who fill more reserved and skeptical towards the system and, perhaps, perspective guests, reduce their property price in order to make their listings competitive and attractive.

Turning to the other price determinants, we found that major such positive determinants of Airbnb houses in Athens are: the status of the owner (that is, if the host is a professional company) and, naturally, the size of the accommodation, as measured by the number of bathrooms, the number of guests that can be served, and whether the accommodation is an entire house. These findings are certainly in accordance with the relevant literature (see Wang and Nicolau 2017 and Magno et al 2017, for instance). The existence of amenities also affects positively (as expected) the rental price asked. We found that for Athens housing market such determinants are availability of air-conditioning and cable TV. If the accommodation is family-friendly also adds a premium on the price, as other scholars too have made it clear (e.g. Dogru and Pekin 2017). Furthermore, taking side with Wang and Nicolau (2017), we found that the allowance of smoking inside the accommodation is associated with lower prices. Surprisingly, none of our models showed availability of breakfast to has a significant effect on price, in contrast with Dogru and Pekin (2017) who supported the opposite. As expected, we also found location to play an important role on price. In particular, in tandem with Zhang et al (2017), Teubner et al (2017), Gibs et al (2018) anh Dogru and Pekin (2017) we concluded that the longer the distance of the property is to either the city center or to a transport hub (such as a metro station), the lower is the price. A cleaning fee and a required minimum length of stay (minimum number of nights) have positive and negative coefficients, respectively, in relation to price. Lastly, host experience also seems to have an impact on the price asked, giving it a premium in comparison to hosts of lower experience.

These findings are certainly useful to hosts looking to enter the market or aiming to increase or to sustain their market share. It is suggested that altering (adding or removing) a specific characteristic in the property under offer or in the host's profile, can have a certain effect in the price that can be asked for. For example, if a house does not have air-conditioning, the host can add an air-condition and the price can be increased by about 25%.

Now let us briefly focus on our second set of models (LOGITs) and the conclusions that these provide. As discussed, these models had a different purpose, i.e. to assess the determinants of host's trust on their prospective guests. First, we found that hosts with a Superhost status are more likely to trust the prospective guests. This means that "good" or "positive" experience with the Airbnb model of sharing economy tends to increase trust to peers. In turn, "bad" or "negative" such experience (reflected, arguably, in the number of low-rated reviews within the Airbnb membership time) increases the possibility hosts to be less likely to trust future guests. As such, time of membership, alone, seems to have a negative effect on trust. We argue that according to our knowledge this is the first time that such an issue is brought to the attention of the limited but growing relevant literature (e.g. Deng and Ravichandran 2017, Ert et al 2016, Hawlitschek et al 2016c, Liang et al 2018, Ma et al 2017, Mittendorf 2017c, Yang et al 2016), and certainly this is an area that needs further research and exploration. Lastly, it is interesting to note that both the gender and the degree of cosmopolitanism of hosts do not seem to play a significant role in affecting trust to peers in the Athens Airbnb case.

Undoubtedly the current research constitutes a very first attempt to explore the role of trust in Athens Airbnb sharing economy model, and in Airbnb housing business model in general. Further studies need to be conducted using not only more advanced techniques but also larger samples (expanded in space and in time). Future work could conduct a comparative analysis with other cities and could do a pricing through the time. On the context of trust of hosts in the potential guests, researchers can add more behavioral characteristics of hosts, acquired through (for example) questionnaires.

# References


Abramova, O., Shanvanova, T., Fuhrer, A., Krasnova, H., Buxmann, P. (2015). Understanding the Sharing Economy: The Role of Response to negative Reviews in the Peer-To-Peer Accommodation Sharing Network. In: ECIS 2015 Proceedings.

Abrate, G., Capriello, A., Franquelli, G. (2011). "When quality signals talk: Evidence from the Turin hotel industry". *Tourism Management*. 32(4), pp. 912-921

Airbnb (2018a). About us. https://press.atairbnb.com/about-us/

Airbnb (2018b). What is the Airbnb service fee?. https://www.airbnb.com/help/article/1857/what-is-the-airbnb-service-fee

Aguiló, E., Riera, A., & Rosselló, J. (2005). The short-term price effect of a tourist tax through a dynamic demand model: The case of the Balearic Islands. *Tourism Management*, 26(3), pp. 359–365. doi:10.1016/j.tourman.2003.07.005

Andersson, D.E. (2000). Hypothesis testing in hedonic price estimation: On the selection of independent variables. *Annals of Regional Science*, 34(2), pp. 293-304.

Arvanitidis, P., Nasioka F. (2017). Urban Open Greenspace as a Commons, An Explanatory Case Study in Greece. *The Public Sector*, 43(1), pp. 19-32

Aufmann, C., (2016). Designing for Trust: Airbnb Design [WWW Document]. Airbnb, URL. http://airbnb.design/designing-for-trust/.

Ba, S., Pavlou, P.A. (2002). Evidence of the effect of trust building technology in electronic markets: price premiums and Buyer behavior. MIS Q. 26, pp. 243–268.

Barron, K.; Kung, E.; Proserpio, D. (2016). The Sharing Economy and Housing Affordability: Evidence from Airbnb

Belk, R. (2010). Sharing. *Journal of Consumer Research*, 36(February), pp. 715–734.

Bostman, R., Rogers, R. (2010). What is mine is yours: How collaborative consumption is changing the way we live. HEC Paris

Bonston Ponte, E., Carvajal-Trujillo, E., & Escobar-Rodríguez, T. (2015). Influence of trust and perceived value on the intention to purchase travel online: integrating the effects of assurance on trust antecedents. *Tourism Management*, 47, pp. 286-302

Bower, J. L., & Christensen, C. M. (1995). Disruptive technologies: Catching the wave. *Harvard Business Review*. 43–53.

Camilleri, J., & Neuhofer, B. (2017). Value co-creation and co-destruction in the Airbnb sharing economy. *International Journal of Contemporary Hospitality Management*, 29(9), pp. 2322-2340.

Clewer, A., Pack, A., Sinclair, M., Johnson, P., & Thomas, B. (1992). Price competitiveness and inclusive tour holidays in European cities. In P. Johnson & B. Thomas (Eds.), Choice and demand in tourism, *Elsevier* (pp. 123–143).

Cohen, B. and Kietzmann, J. (2014). Ride On! Mobility Business Models for the Sharing Economy. *Organization & Environment*, 27(3), pp. 279–296

Court, A., T. (1939). Hedonic price indexes with automotive examples, in The Dynamics of Automobile Demand. General Motors, New York

Chen, C., Rothschild, R. (2010). An application of hedonic pricing analysis to the case of hotel rooms in Taipei. *Tourism Economics*. 16(3), pp. 685–694

Chica, M., Chiong, R., Adam, M.T.P., Damas, S., Teubner, T. (2017). An evolutionary trust game for the sharing economy. IEEE Congr. Evol. Comput. CEC 2017 – Proc. 2510–2517. doi:10.1109/CEC.2017.7969610

Choi, K., Jung, J., Ryn, S., Kim, S., Yoon, S. (2015). The relationship between Airbnb and the Hotel Revenue: In the case of Korea. *Indian Journal of Science and Technology*. 8(26), pp. 1-8

Christensen, C. M. (1997). The innovator's dilemma: When new technologies cause great firms to fail. Boston, MA: *Harvard Business School Press*

Deng, C., Ravichandran, T., (2017). How Consumers Perceive Trustworthiness of Providers in Sharing Economy: Effects of Photos and Comments on Demand at Airbnb. In: AMCIS 2017 Proceedings.

Diekmann, A., Jann, B., Przepiorka, W., Wehrli, S. (2014). Reputation formation and the evolution of cooperation in anonymous online markets. *American Sociological Review* 79, 1 (2014), 65–85.

Dolnicar, S. and Otter, T. (2003). Which hotel attributes matter? A review of previous and a framework for future research, in Griffin, T. and Harris, R. (Eds), Proceedings of the 9th Annual Conference of the Asia Pacific TourismAssociation (APTA), University of Technology Sydney, pp. 176-188.

Edelman, B. G., Luca, M. (2014). Digital Discrimination: The Case of Airbnb.com. *Harvard Business School* NOM Unit Working Paper No. 14-054

Edelman, B. G., Geradin D. (2015). Efficiencies and regulatory shortcuts: How should we regulate companies like Airbnb and Uber. *Stanford Technology Law Review* 293, pp. 1-33

Ert, E., Fleischer, A. (2017). What in a photo makes you trust a person online? A structural equation modeling approach. SSRN Electron. J. https://doi.org/10.2139/ssrn.2992043.

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

Espinet, J. M., Saez, G., Coenders, G., Fluvia, M. (2003). Effect on Prices of the Attributes of Holiday Hotels: A Hedonic Prices Approach. *Tourism Economics*. 9(2), pp. 165-177

Fang, B., Ye, Q., Law, R. (2016). Effect of sharing economy on tourism industry employment. *Annals of Tourism Research*. 57, pp. 264–267.

Flabbia, L., and A. Maroc. (2012). The effect of job flexibility on female labor market outcomes: Estimates from a search and bargaining model. *Journal of Econometrics* 168(1), pp. 81-95.

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

Fradkin, A., Grewal, E., Holtz, D., Pearson, M. (2015). Bias and Reciprocity in Online Reviews: Evidence From Field Experiments on Airbnb. Proceedings of the Sixteenth ACM Conference on Economics and Computation. pp 641-641

García-Pozo, A. (2009). A nested housing market structure: Additional evidence. *Housing Studies* 24(3), pp. 373-98.

Goldhaber, D., K. Destler, and D. Player. 2010. Teacher labor markets and the perils of using hedonics to estimate compensating differentials in the public sector. *Economics of Education Review* 29(1), pp. 1-17.

Goodman, A. (1978). Hedonic prices, price indices and housing markets. *Journal of Urban Economics*, 5(4), pp. 471–484. doi: 10.1016/0094-1190(78)90004-9

Goodman, A., & Thibodeau, T. (2003). Housing market segmentation and hedonic prediction accuracy. *Journal of Housing Economics*, 12(3), pp. 181–201. doi: 10.1016/S1051-1377(03)00031-7

Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., Goddwill, A. (2018). Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. *Journal of Travel & Tourism Marketing*. 35(1), pp. 46-56

Griliches, Z. (1961). Hedonic price indexes for automobiles: An econometric analysis of quality change. In The price statistics of the federal government, 173-96. New York: National Bureau of Economic Research.

Griliches, Z. (1971). Hedonic price indexes revisited, in "Price Indexes and Quality Change" (Griliches, Ed), Harvard, Cambridge, Massachusetts

Griliches, Z. (1971). Hedonic price indices for automobiles: an econometric analysis of quality change, in Price Indexes and Quality Chang (Griliches, Ed.), Harvard, Cambridge, Massachusetts

Gutt, D., Herrmann, P. (2015). Sharing Means Caring? Hosts' Price Reaction to Rating Visibility. ECIS 2015 Research-in-Progress Papers. Paper 54.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*. 18(12), pp. 1192-1217

Guttentag, D., Smith, S. (2017). Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. *International Journal of Hospitality Management*. 64, pp. 1-10

Guttentag, D. (2016). Why tourists choose Airbnb: A motivation-based segmentation study underpinned by innovation concepts. UWSpace. http://hdl.handle.net/10012/10684

Guttentag, D., Smith, S., Potwarka, L., Havitz, M. (2017). Why Tourists Choose Airbnb: A Motivation-Based Segmentation Study. *Journal of Travel Research*. 54(3), pp.1-18

Haas, G. C. (1922). Sale Prices as a Basis for Farm Land Appraisal, Technical Bulletin 9. St. Paul: *The University of Minnesota Agricultural Experiment Station*, pp. 1-57

Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American Economic Review*. 70(3), pp. 474–475.

Han, H., Koo, C., Chung, N. (2016). Implication of the fit between Airbnb and host characteristics. In: ICEC 2016 Proceedings. doi:10.1145/2971603.2971613

Hawlitschek F., Notheisen B., Teubner, T. (2018). The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy. *Electronic Commerce Research and Applications*. 29 pp. 50 – 63

Hawlitschek, F., Teubner, T., Gimpel, H. (2016a). Understanding the sharing economy – Drivers and impediments for participation in peer-to-peer rental. In: HICSS 2016 Proceedings. pp. 4782–4791.

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

Heinrichs, H. (2013). Sharing Economy: A potential new pathway to sustainability. GAIA - Ecological Perspectives for Science and Society, 22(4) pp. 228-231

Hofmann, E., Hartl, B., Penz, E. (2017). Power versus trust – what matters more in collaborative consumption? *Journal of Services. Mareting.* 31, pp. 589–603. F.https://doi.org/10.1108/JSM-09-2015-0279.

Houthakker, H. (1952). Compensated changes in quantities and qualities consumed. *Review of Economic Studies* 19(3), pp. 155-64.

Ikkala, T. (2014). Monetary Network Hospitality and Sociability: A Study of Hospitality Exchange in the Context of Airbnb. University of Helsinki (Master's thesis)

Jia J., Wagman L. (2018). The Impact of Seller Transaction Unreliability: Evidence from Airbnb. Illinois Institute of Technology

Johnson, A.-G., Neuhofer, B. (2017). Airbnb e an exploration of value co-creation experiences in Jamaica. *International Journal of Contemporary Hospitality Management*, 29(9), pp.2361-2376.

Juaneda, C., Raya, J. M., Sastre, F. (2011). Pricing the Time and Location of a Stay at a Hotel or Apartment. *Tourism Economics*. 17(2), pp. 321–338

Kakar, V., Franco, J., Voelz, J., Wu, J. (2016). The Visible Host: Does Race guide Airbnb rental rates in San Francisco? San Francisco State University

Karlsson, L., Dolnicar, S. (2016). Someone's been sleeping in my bed. *Annals of Tourism Research*. 58 pp.159-162

Kamal, P., Chen, J.Q. (2016). Trust in Sharing Economy. In: PACIS 2016 Proceedings

Kim, J., Yoon, Y., Zo, H. (2015). Why People Participate in the Sharing Economy: A Social Exchange Perspective. In: PACIS 2015 Proceedings.

Kim, M.-J., Chung, N., Lee, C.-K. (2011). The effect of perceived trust on electronic commerce: shopping online for tourism products and services in South Korea. *Tourism Management*, 32(2), pp. 256-265

Kuminoff, N.V., Parmeter, C.F., Pope, J.C. (2010). Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? *Journal of Environmental Economics and Management* 60, pp.145-60.

Lampinen, A., Cheshire, C. (2016). Hosting via Airbnb: Motivations and Financial Assurances in Monetized Network Hospitality. CHI '16 Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. pp. 1669-1680

Lancaster, K., J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy.* 74(2), pp. 132-157.

Le Jeune, S. (2016). The Sharing Economy (2016.). Schroders. Available at: http://www.schroders.com/en/SysGlobalAssets/digital/resources/pdfs/2016-08-thesharing-economy.pdf (Accessed: 15/03/2017)

Lee, D. Hynn, W., Ryu, J., Lee, W., Rhee, W., Suh, B. (2015). An analysis of social features associated with room sales of Airbnb. Proceedings of the 18th ACM Conference Companion on Computer Supported Cooperative Work & Social Computing. 14-18

Lessig, L. (2008). Remix: Making Art and Commerce Thrive in the Hybrid Economy. Penguin Press

Li, Y., Pan, Q. Yang, T., Guo, L. (2016). Reasonable price recommendation on Airbnb using Multi-Scale clustering. In Proceedings of the 2016 35th Control Conference (CCC), Chengdu, China, 27–29 July 2016; pp. 7038–7041.

Liang, L.J., Choi, H.C., Joppe, M. (2018). Exploring the relationship between satisfaction, trust and switching intention, repurchase intention in the context of Airbnb. *International Journal of Hospitality Management*. 69, pp. 41–48. https://doi.org/10.1016/j.ijhm.2017.10.015.

Liang, L.G., Choi, H.S.C., Joppe, M. (2018). Understanding repurchase intention of Airbnb consumers: perceived authenticity, electronic word-of-mouth, and price sensitivity. *Journal of Travel & Tourism Marketing*. 35(1), pp. 73-89

Liang, L.J. (2015). Understanding repurchase intention of Airbnb consumers: Perceived authenticity, EWoM and price sensitivity (Unpublished Master's Thesis). University of Guelph.

Livingston, J.A. (2005). How valuable is a good reputation? A sample selection model of internet auctions. *The Review of Economics and Statistics* 87(3), pp. 453–465.

Lu, Y., Zhao, L., Wang, B. (2010). From virtual community members to C2C ecommerce buyers: Trust in virtual communities and its effect on consumers' purchase intention. *Electronic Commerce Research and Applications*. Appl. 9, pp. 346–360. https://doi.org/10.1016/j.elerap.2009.07.003.

Ma, X., Hancock, J.T., Lim Mingjie, K., Naaman, M. (2017). Self-Disclosure and Perceived Trustworthiness of Airbnb Host Profiles. In: CSCW 2017 Proceedings. pp. 2397–2409. doi:10.1145/2998181.2998269

Malhotra, A. and Van Alstyne, M. (2014). The dark side of the sharing economy … and how to lighten it. *Communications of the ACM*, 57(11), pp. 24–27.

Malpezzi, S. (2002). Hedonic price models: a selective and applied review. *The Center for Urban Land Economics Research* , pp. 67-89

Malpezzi, S. (2003). Hedonic price models: a selective and applied review. In: O'Sullivan, A. and Gibb, K. (eds.) Housing Economics and Public Policy: Essays in Honour of Duncan Maclennan. Malden MA: Blackwell, pp. 67–89

Mangion, M., Durbarry, R., Sinclair, M. (2005). Tourism competitiveness: Price and quality Tourism competitiveness: Price and quality. *Tourism Economics*, 11(1), pp. 45–68. doi:10.5367/0000000053297202

Manning, K. C., Bearden,W. O., Madden, T. J. (1995). Consumer innovativeness and the adoption process. *Journal of Consumer Psychology*, 4(4), pp. 329-345.

Mao, Z., Lyu, J. (2017). Why travelers use Airbnb again? *International Journal of Contemporary Hospitality Management*, 29(9), pp. 2464-2482.

McKnight, D. H., Chervany, N. L. (2001). What Trust Means in E-Commerce Customer Relationships: An Interdisciplinary Conceptual Typology. *International Journal of Electronic Commerce*, 6(2), pp. 35–59.

Melnik, I., M., Alm, J. (2002). Does a seller's ecommerce reputation matter? Evidence from eBay auctions. *The journal of industrial economics* 50(3), pp. 337–349.

Mittendorf, C. (2017a). Societal Transformation through the Sharing Economy: An example of Trust and Risk on Couchsurfing (pretest). In: PACIS 2017 Proceedings. pp. 1–13.

Mittendorf, C. (2017b). How Trust and Risk Influence Sharing Intentions on Airbnb? Completed Research Paper. In: PACIS 2017 Proceedings. p. 13.

Mittendorf, C. (2016). What Trust means in the Sharing Economy: A provider perspective on Airbnb.com. In: AMCIS 2016 Proceedings.

Teubner, T., Hawlitschek, F. (2018). The Economics of Peer-to-Peer Online Sharing. In: The Rise of the Sharing Economy: Exploring the Challenges and Opportunities of Collaborative Consumption. ABC-CLIO, pp. 129–156.

Magno, F., Cassia, F., Ugolini, M. (2017). Factors influencing prices on accommodation sharing platforms: The effects of host's experience and market demand. 20th Excellence in Services University of Verona. ISBN 9788890432774

Mody, M. A., Suess, C., Lehto, X. (2017). The accommodation experiencescape: A comparative assessment of hotels and Airbnb. *International Journal of Contemporary Hospitality Management*, 29(9), pp. 2377-2404.

Möhlmann, M. (2015). Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behavior*. 14, pp. 193–207. https://doi.org/10.1002/cb.1512.

Monty, B., Skidmore, M. (2003). Hedonic Pricing and Willingness to Pay for Bed and Breakfast Amenities in Southeast Wisconsin. *Journal of Travel Research*. 42(2), pp. 195–199

Morgan, R. M., Hunt, S. D. (1994). The Commitment-Trust - Theory of Relationship Marketing, *Journal of Marketing*, 58(3), pp. 20–38.

Neeser, D., Peitz, M., Stuhler, J. (2015). Does Airbnb hurt hotel business: Evidence from the Nortic countries. Universidad Carlos III de Madrid

Nelson, J. P. (2004). Meta-analysis of airport noise and hedonic property values. *Journal of Transport Economics and Policy* 38(1), pp. 1-27.

Nesta, N. (2015). The titans of the sharing economy meet their match [WWW Document]. http://www.nesta.org.uk. URL http://www.nesta.org.uk/2016- predictions/titans-sharing-economy-meet-match

Nowak, B., T. Allen, J. Rollo, V. Lewis, L. He, A. Chen, W. N. Wilson, M. Costantini, O. Hyde, K. Liu, M. Savino, B. A. Chaudhry, A. M. Grube, and E. Young. (2015). Global Insight: Who Will Airbnb Hurt More—Hotels or OTAs? Morgan Stanley Research. http://linkback.morganstanley.com/web/sendlink/webapp/f/9lf3j168-3pcc-g01h-b8bf
005056013100?store=0&d=UwBSZXNlYXJjaF9NUwBiNjVjYzAyNi04NGQ2LTExZTUtYj

FlMi03YzhmYTAzZWU4ZjQ%3D&user=bdvpwh9kcvqs-49&__gda__=1573813969_cf5a3761794d8651f8618fc7a544cb82.

Nunes, M., Correia, J. (2013). Improving trust using online credibility sources and social network quality in P2P marketplaces. *Information Systems and Technology* (CISTI), 2013 8th Iber. Conf. 1–4.

Papadopoulou P., Andreou A., Kanellis P., Martakos D. (2001). Trust and relationship building in electronic commerce. *Internet Research* 11(4), pp. 322–332.

Philip, H.E., Ozanne, L.K., Ballantine, P.W. (2015). Examining temporary disposition and acquisition in peer-to-peer renting. *Journal of Marketing and Management*. 31, pp. 1310–1332.https://doi.org/10.1080/0267257X.2015.1013490.

Poon, K.Y., Huang, W.-J. (2017). Past experience, traveler personality and tripographics on intention to use Airbnb. *International Journal of Contemporary Hospitality Management*, 29(9), pp. 2425-2443.

Portolan, A. (2013). Impact of the attributes of private tourist accommodation facilities onto prices: A hedonic price approach. *European Journal of Tourism Research*. 6(1), pp. 74-82.

Resnick, P., Zeckhauser, R., Swanson, J., Lockwood, K. (2006). The value of reputation on eBay: controlled experiment. *Experimental economics* 9(2), pp. 79–101.

Resnick, P., Zeckhauser, R. (2002). Trust among strangers in Internet transactions: empirical analysis of eBay's reputation system. *Advances in Applied Microeconomics*, 11, pp. 127-157.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *The Journal of Political Economy*. 82(3455), pp. 34-55.

Saló, A., 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

Sánchez-Ollero, J.L., García-Pozo, A., Marchante-Mera, A. (2013). How does respect for the environment affect final prices in the hospitality sector? A hedonic pricing approach. *Cornell Hospitality Quarterly*. DOI: 1938965513500709.

Satama, S. (2014). Consumer adoption of access-based consumption services-Case Airbnb (Unpublished Master's Thesis). Finland: Aalto University.

Segu, M. (2018). Do short-term rent platforms affect rents? Evidence from Airbnb in Barcelona. University of Paris Sud

Sirmans, G.S., Macpherson A.D. (2003). The composition of Hedonic Pricing Models: a review of the literature. National Association of Realtors

Small, K.A., Steimetz S.C. (2012). Spatial hedonics and the willingness to pay for residential amenities. *Journal of Regional Science* 52(4), pp. 635-47.

Smith, C. (2018). 100 Airbnb statistics and facts (June 2018): By the numbers. DMR. https://expandedramblings.com/index.php/airbnb-statistics/

So, K., K., F., Oh, H., Min., S. (2018). Motivations and constraits of Airbnb consumers: Findings from a mixed methods approach. *Tourism Management*. 67, pp. 224 – 236

Taylor, P. (1995). Measuring changes in the relative competitiveness of package tour destinations. *Tourism Economics*, 1(2), pp. 169–182.

Teubner, T. (2014). Thoughts on the sharing economy. In: MCCSIS 2014 Proceedings. pp. 322–326

Teubner, T., Saade, N., Hawlitschek, F., Weinhardt, C. (2016). It's only pixels, badges, and stars: On the economic value of reputation on Airbnb. In: ACIS 2016 Proceedings.

Teubner, T., Hawlitschek, F. (2018). The Economics of Peer-to-Peer Online Sharing. In: The Rise of the Sharing Economy: Exploring the Challenges and Opportunities of Collaborative Consumption. ABC-CLIO, pp. 129–156.

Teubner, T., Hawlitschek, F., Dann, D. (2017). Price determinants on Airbnb: How reputation pays of in the Sharing Economy. *Journal of Self – Governance and Management Economics*. 5(4), pp. 53-80

Thrane, C. (2007). Examining the determinants of room rates for hotels in capital cities: The Oslo experience. *Journal of Revenue and Pricing Management*. 5(4), pp. 315 – 323

Thrane, C. (2005). Hedonic price models and sun-and-beach package tours: the Norwegian case. *Journal of Travel Research*. Vol. 43, No 3, pp. 302-308.

Tinbergen, J. (1956) On the theory of income distribution. *Weltwirtschaftliches Archiv*, 77(2), pp. 155-75.

Tussyadiah, I. (2015). An Exploratory Study on Drivers and Deterrents of Collaborative Consumption in Travel. In Information & Communication Technologies in Tourism 2015, edited by I. Tussyadiah and A. Inversini, 817–30. Switzerland: Springer International.

Tussyadiah, I.P., Pesonen, J. (2016a). Drivers and barriers of peer-to-peer accommodation stayean exploratory study with American and Finnish travelers. *Current Issues in Tourism*, 21(6)1-18.

Yang, S., Ahn, S. (2016). Impact of motivation in the sharing economy and perceived security in attitude and loyalty toward Airbnb. *Advanced Science and Technology Letters*, 129, pp. 180-184.

Yang, S., Lee, K., Lee, H., Koo, C. (2016). Trust Breakthrough in the sharing economy: An empirical study of Airbnb. In: PACIS 2016 Proceedings. pp. 131.

Ye, T., Alahmad, R., Pierce, C., Robert Jr, L.P. (2017). Race and Rating on Sharing Economy Platforms: The Effect of Race Similarity and Reputation on Trust and Booking Intention in Airbnb. In: ICIS 2017 Proceedings.

Wallace, H.A. (1926). Comparative Farmland Values in Iowa. *Journal of Land and Public Utility Economics.* 2, pp. 385-392.

Wang, D., Nicolau, L.J. (2017). Price determinants of Sharing Economy Based Accommodation Rental: A Study of Listings from 33 Cities on Airbnb.com. *Intenational Journal of Hospitality Management*. 62, pp. 120-131

Waught, F.V. (1928). Quality factors influencing vegetable prices. *Journal of Farm Economics* 10(2), pp. 185-96.

Witte, A., Sumka, H., Erekson, H. (1979). An estimate of a structural hedonic price model of the housing market: An application of Rosen's theory of implicit markets. *Econometrica: Journal of the Econometric Society*, 47, pp. 1151–1173. doi:10.2307/1911956

Wu, J., Zeng, M., Xie, K.L. (2016). Chinese travelers’ behavioral intentions toward room-sharing platforms. *International Journal of Contemporary Hospitality Management*. 29, pp. 2688–2707. https://doi.org/10.1108/IJCHM-08-2016-0481.

Zhang, Z., Chen, J., C., R., Han, D., L., Yang, L. (2017). Key Factors Affecting the Price of Airbnb Listings: A Geographically Weighted Approach. *Sustainability*, 9(9), pp. 1-13

Zhang, Z., Ye, Q., Law, R. (2011). Determinants of hotel room price: An exploration of travelers' hierarchy of accommodation needs. *International Journal of Contemporary Hospitality Management*. 23(7), pp.972-981

Zervas, G., Proserpio, D., Byers, J. (2015). A First Look at Online Reputation on Airbnb, Where Every Stay is Above Average. Available at SSRN: https://ssrn.com/abstract=2554500 or http://dx.doi.org/10.2139/ssrn.2554500

Zervas, G., Proserpio, D., Byers, J., W. (2017). The rise of Sharing Economy: Estimating the impact of Airbnb on the hotel industry. *Intenational Journal of Market Research*, 54(5), pp. 687-705

Χάλκος, Γ. (2011). Οικονομετρία: Θεωρία, εφαρμογές και χρήση προγραμμάτων σε Η/Υ. Gutenberg

# Appendix

Table 4: Descriptive statistics of variables of Study 1.

| Variable | Average | St.dev | Median | Min | Max |
|---|---|---|---|---|---|
| Price | 69,82 | 68,706 | 50 | 9 | 526 |
| ***Property attributes*** | | | | | |
| Guests | 4,0675 | 2,3799 | 4 | 1 | 16 |
| Bathrooms | 1,3601 | 0,6725 | 1 | 0,5 | 5,5 |
| Bedrooms | 1,6334 | 0,966 | 1 | 0 | 7 |
| Entire home | 0,7572 | 0,4287 | 1 | 0 | 1 |
| ***Accommodation amenities*** | | | | | |
| Air-conditioning | 0,7184 | 0,4497 | 1 | 0 | 1 |
| Breakfast | 0,2297 | 0,4206 | 0 | 0 | 1 |
| Family-friendly | 0,7508 | 0,4325 | 1 | 0 | 1 |
| Cable TV | 0,1197 | 0,3246 | 0 | 0 | 1 |
| Smoking | 0,3818 | 0,4861 | 0 | 0 | 1 |
| ***Location (distances)*** | | | | | |
| City center | 1727,657 | 963,1929 | 1615,648 | 43,0961 | 5694,45 |
| Metro | 556,7031 | 309,2394 | 492,6047 | 21,1962 | 1566,273 |
| ***Neighborhood qualities*** | | | | | |
| Density | 18429,44 | 7647,912 | 18670,78 | 7827,52 | 31689,91 |
| ***"Contract" terms (rules)*** | | | | | |
| Cleaning fee | 17,881 | 16,3956 | 15 | 0 | 80 |
| Minimum nights | 2,0514 | 2,4919 | 2 | 1 | 28 |
| 24 hour check-in | 0,3268 | 0,469 | 0 | 0 | 1 |
| Instant booking | 0,4612 | 0,4984 | 0 | 0 | 1 |
| ***Host attributes*** | | | | | |
| Membership | 960,9355 | 586,4922 | 810 | 7 | 2274 |
| Company | 0,0353 | 0,1847 | 0 | 0 | 1 |
| ***Reputation & trust attributes*** | | | | | |
| Number of reviews | 29,2186 | 46,2651 | 8 | 0 | 425 |
| Review score | 94,193 | 7,6168 | 96 | 40 | 100 |
| Verified ID | 0,5032 | 0,4999 | 1 | 0 | 1 |

Table 5: Hedonic Price Models

| DV: Log (Price) | | | |
|---|---|---|---|
| **Variable** | **OLS1** | **OLS2** | **OLS3** |
| Constant | 3.039281 (9.625) *** | 3.032304 (9.837) *** | 2.977823 ( 9.699) *** |
| ***Property attributes*** | | | |
| Guests | 0.076530 (4.154) *** | 0.076426 (4.163) *** | 0.074868 ( 4.074) *** |
| Bathrooms | 0.266884 (5.617) *** | 0.267763 ( 5.735) *** | 0.274558 ( 5.886) *** |
| Bedrooms | 0.036659 (0.831) | 0.036673 ( 0.833) | 0.029276 ( 0.667) |
| Entire home | 0.270151 (4.132) *** | 0.269420 ( 4.153) *** | 0.275076 ( 4.288) *** |
| ***Accommodation Amenities*** | | | |
| Air-conditioning | 0.240699 (4.418) *** | 0.240391 (4.427) *** | 0.242694 ( 4.460) *** |
| Breakfast | 0.089003 (1.613) + | 0.088346 (1.615) + | 0.084006 ( 1.533) + |
| Cable TV | 0.137645 (1.927) * | 0.137389 (1.929) * | 0.106063 ( 1.791) * |
| Family- friendly | 0.105854 (1.786) * | 0.105547 (1.787) * | 0.123463 ( 1.741) * |
| Smoking | -0.15220 (-2.942)*** | -0.15381 (-2.995)*** | -0.142848 (-2.837)*** |
| ***Location (distances)*** | | | |
| City center | -0.00017 (-5.614)*** | -0.000177 (-5.625) *** | -0.000191 (-6.252)*** |
| Metro | -0.000126 (-1.439) | -0.000126 (-1.439) | -0.000180 ( -2.272)** |
| ***Neighborhood qualities*** | | | |
| Density | -7.14E-06 (-1.364) | -7.15E-06 (-1.370) | |
| ***"Contract" terms (rules)*** | | | |
| Cleaning fee | 0.004988 (2.736) *** | 0.004997 (2.750) *** | 0.005031 (2.793) *** |
| Minimum nights | -0.034348 (-1.810) * | -0.034180 (-1.811) * | -0.033944 (-1.811)* |
| 24 hour check-in | -0.062200 (-1.221) | -0.06158 ( -1.220) | |
| Instant booking | -0.005178 (-0.106) | | |
| ***Host attributes*** | | | |
| Membership | 9.15E-05 (2.210) ** | 9.20E-05 (2.242) ** | 8.66E-05 (2.114) ** |
| Company | 0.303257 (1.936) * | 0.301699 (1.938) * | 0.302366 (1.952) * |
| ***Reputation & trust attributes*** | | | |
| Review score | 0.001305 (0.406) | 0.001344 ( 0.422) | 0.001379 (0.432) |
| Number of reviews | -0.000125 (-0.245) | -0.000130 (-0.257) | -0.000128 (-0.253) |
| Verified ID | -0.080771 (-1.689) * | -0.081166 (-1.706) * | -0.079144 ( -1.662) * |
| | | | |
| Adj. $R^2$ | 74,874% | 74,979% | 74,85% |
| AIC | 0.845439 | 0.837675 | 0.835456 |
| F – value | 37.18500 | 39.20863 | 43.17549 |
| Prob. (F – value) | 0.000000 | 0.000000 | 0.000000 |
| N | 256 | 256 | 256 |

Table 5 (Cont.)

| DV: Log (Price) | |
|---|---|
| **Variable** | **OLS4** |
| Constant | 2.998220 (9.765) *** |
| ***Property attributes*** | |
| Guests | 0.081544 (5.800) *** [8,4961%] |
| Bathrooms | 0.286460 (6.485) *** [33,1705%] |
| Bedrooms | |
| Entire home | 0.267830 (4.180) *** [30,7125%] |
| ***Accommodation Amenities*** | |
| Air-conditioning | 0.228439 (4.250) *** [25,6637%] |
| Breakfast | |
| Family friendly | 0.133536 (1.888) * [14,2862%] |
| Cable TV | 0.111585 (1.885) * [11,8049%] |
| Smoking | -0.142240 (-2.824) ***[14,2862%] |
| ***Location (distances)*** | |
| City center | -0.000188 (-6.158) *** [-0,0188%] |
| Metro | -0.000175 (-2.206) ** [-0,0175%] |
| ***Neighborhood qualities*** | |
| Density | |
| ***"Contract" terms (rules)*** | |
| Cleaning fee | 0.005333 (3.018) *** [0,5347%] |
| Minimum nights | -0.036495 (-1.962) * [-3,5837%] |
| 24 hour check-in | |
| Instant booking | |
| ***Host attributes*** | |
| Membership | 8.20E-05 (2.003) ** [0,0082%] |
| Company | 0.296698 (1.927) * [34,5409%] |
| ***Reputation & trust attributes*** | |
| Review score | 0.001555 (0.488) |
| Number of reviews | -0.000203 (-0.405) |
| Verified ID | -0.085086 (-1.795) * [-8,1567%] |
| | |
| Adj. $R^2$ | 74,782% |
| AIC | 0.831169 |
| F – value | 48.26168 |
| Prob. (F – value) | 0.000000 |
| N | 256 |

OLS1 model.

Dependent Variable: LOGPRICE
Method: Least Squares
Date: 08/28/18 Time: 08:32
Sample (adjusted): 1 311
Included observations: 256 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3.039281 | 0.315762 | 9.625232 | 0.0000 |
| GUESTS | 0.076530 | 0.018420 | 4.154821 | 0.0000 |
| BATHS | 0.266884 | 0.047507 | 5.617732 | 0.0000 |
| BEDROOMS | 0.036659 | 0.044085 | 0.831539 | 0.4065 |
| ROOM_TYPE | 0.270151 | 0.065370 | 4.132676 | 0.0000 |
| AIR_CONDITION | 0.240699 | 0.054481 | 4.418034 | 0.0000 |
| BREAKFAST | 0.089003 | 0.055163 | 1.613472 | 0.1080 |
| FAMILY_FRIENDLY | 0.105854 | 0.059254 | 1.786448 | 0.0753 |
| CABLE_TV | 0.137645 | 0.071409 | 1.927566 | 0.0551 |
| SMOKING | -0.152202 | 0.051730 | -2.942230 | 0.0036 |
| DIAST_SINT | -0.000177 | 3.16E-05 | -5.614468 | 0.0000 |
| DIST_METRO | -0.000126 | 8.77E-05 | -1.439862 | 0.1512 |
| DENSITY | -7.14E-06 | 5.23E-06 | -1.364246 | 0.1738 |
| CLEAN_FEE | 0.004988 | 0.001822 | 2.736722 | 0.0067 |
| MIN_NIGHTS | -0.034348 | 0.018972 | -1.810490 | 0.0715 |
| _24H_CHECK_IN | -0.062200 | 0.050910 | -1.221758 | 0.2230 |
| INSTANT_BOOKING | -0.005178 | 0.048582 | -0.106582 | 0.9152 |
| MEMBERSHIP | 9.15E-05 | 4.14E-05 | 2.210992 | 0.0280 |
| COMPANY | 0.303257 | 0.156640 | 1.936014 | 0.0541 |
| NUM_REV | -0.000125 | 0.000508 | -0.245248 | 0.8065 |
| REVIEW_SCORE | 0.001305 | 0.003207 | 0.406992 | 0.6844 |
| VERIFIED_ID | -0.080771 | 0.047795 | -1.689951 | 0.0924 |

| | | | |
|---|---|---|---|
| R-squared | 0.769432 | Mean dependent var | 3.956081 |
| Adjusted R-squared | 0.748740 | S.D. dependent var | 0.707092 |
| S.E. of regression | 0.354436 | Akaike info criterion | 0.845439 |
| Sum squared resid | 29.39616 | Schwarz criterion | 1.150102 |
| Log likelihood | -86.21615 | Hannan-Quinn criter. | 0.967973 |
| F-statistic | 37.18500 | Durbin-Watson stat | 2.190694 |
| Prob(F-statistic) | 0.000000 | | |

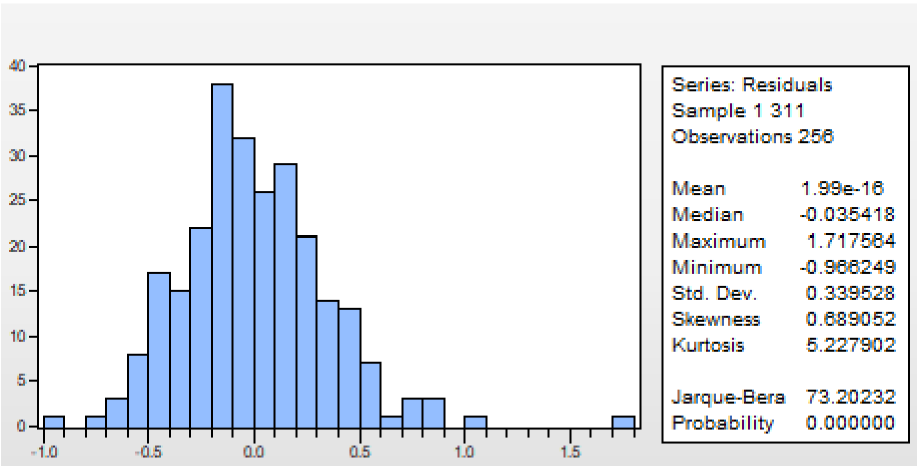
Heteroscedasticity test of OLS1 model.

Heteroskedasticity Test: White

| | | | |
|---|---|---|---|
| F-statistic | 1.864070 | Prob. F(227,28) | 0.0257 |
| Obs*R-squared | 240.1115 | Prob. Chi-Square(227) | 0.2627 |
| Scaled explained SS | 424.0916 | Prob. Chi-Square(227) | 0.0000 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/28/18 Time: 10:29
Sample: 1 311
Included observations: 256
Collinear test regressors dropped from specification

Normality test of OLS1



Multicollinearity test of OLS1

Variance Inflation Factors
Date: 08/28/18 Time: 10:34
Sample: 1 313
Included observations: 256

| Variable | Coefficient Variance | Uncentered VIF | Centered VIF |
|---|---|---|---|
| C | 0.099706 | 203.1816 | NA |
| GUESTS | 0.000339 | 15.50510 | 3.896014 |
| BATHS | 0.002257 | 10.73909 | 2.117566 |
| BEDROOMS | 0.001944 | 14.74360 | 3.827978 |
| ROOM_TYPE | 0.004273 | 6.530981 | 1.632745 |
| AIR_CONDITION | 0.002968 | 4.394687 | 1.201672 |
| BREAKFAST | 0.003043 | 1.477559 | 1.125484 |
| FAMILY_FRIENDLY | 0.003511 | 5.366105 | 1.341526 |
| CABLE_TV | 0.005099 | 1.339491 | 1.166822 |
| SMOKING | 0.002676 | 2.002358 | 1.267117 |
| DIAST_SINT | 9.99E-10 | 6.611050 | 1.398215 |
| DIST_METRO | 7.70E-09 | 5.957625 | 1.418853 |
| DENSITY | 2.74E-11 | 9.693652 | 1.572486 |
| CLEAN_FEE | 3.32E-06 | 3.908157 | 1.616149 |
| MIN_NIGHTS | 0.000360 | 3.727413 | 1.223539 |
| _24H_CHECK_IN | 0.002592 | 1.856866 | 1.204061 |
| INSTANT_BOOKING | 0.002360 | 2.329694 | 1.201249 |
| MEMBERSHIP | 1.71E-09 | 4.482059 | 1.221485 |
| COMPANY | 0.024536 | 1.171876 | 1.144410 |
| NUM_REV | 2.58E-07 | 1.890836 | 1.249944 |
| REVIEW_SCORE | 1.03E-05 | 187.6598 | 1.182043 |
| VERIFIED_ID | 0.002284 | 2.491221 | 1.158028 |

OLS 2 Model

Dependent Variable: LOGPRICE
Method: Least Squares
Date: 10/27/18 Time: 20:36
Sample (adjusted): 1 311
Included observations: 256 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3.032304 | 0.308251 | 9.837120 | 0.0000 |
| GUESTS | 0.076426 | 0.018355 | 4.163809 | 0.0000 |
| BATHS | 0.267763 | 0.046687 | 5.735287 | 0.0000 |
| BEDROOMS | 0.036673 | 0.043992 | 0.833619 | 0.4053 |
| ROOM_TYPE | 0.269420 | 0.064871 | 4.153146 | 0.0000 |
| AIR_CONDITION | 0.240391 | 0.054290 | 4.427915 | 0.0000 |
| BREAKFAST | 0.088346 | 0.054701 | 1.615062 | 0.1076 |
| FAMILY_FRIENDLY | 0.105547 | 0.059059 | 1.787139 | 0.0752 |
| CABLE_TV | 0.137389 | 0.071218 | 1.929132 | 0.0549 |
| SMOKING | -0.151381 | 0.051046 | -2.965578 | 0.0033 |
| DIAST_SINT | -0.000177 | 3.15E-05 | -5.625627 | 0.0000 |
| DIST_METRO | -0.000126 | 8.74E-05 | -1.439100 | 0.1515 |
| DENSITY | -7.15E-06 | 5.22E-06 | -1.370362 | 0.1719 |
| CLEAN_FEE | 0.004997 | 0.001817 | 2.750411 | 0.0064 |
| MIN_NIGHTS | -0.034180 | 0.018866 | -1.811696 | 0.0713 |
| _24H_CHECK_IN | -0.061580 | 0.050470 | -1.220127 | 0.2236 |
| MEMBERSHIP | 9.20E-05 | 4.10E-05 | 2.242709 | 0.0258 |
| COMPANY | 0.301699 | 0.155628 | 1.938592 | 0.0537 |
| NUM_REV | -0.000130 | 0.000505 | -0.257289 | 0.7972 |
| REVIEW_SCORE | 0.001344 | 0.003179 | 0.422612 | 0.6730 |
| VERIFIED_ID | -0.081166 | 0.047551 | -1.706908 | 0.0892 |

| | | | |
|---|---|---|---|
| R-squared | 0.769421 | Mean dependent var | 3.956081 |
| Adjusted R-squared | 0.749797 | S.D. dependent var | 0.707092 |
| S.E. of regression | 0.353689 | Akaike info criterion | 0.837675 |
| Sum squared resid | 29.39759 | Schwarz criterion | 1.128490 |
| Log likelihood | -86.22237 | Hannan-Quinn criter. | 0.954640 |
| F-statistic | 39.20863 | Durbin-Watson stat | 2.193066 |
| Prob(F-statistic) | 0.000000 | | |

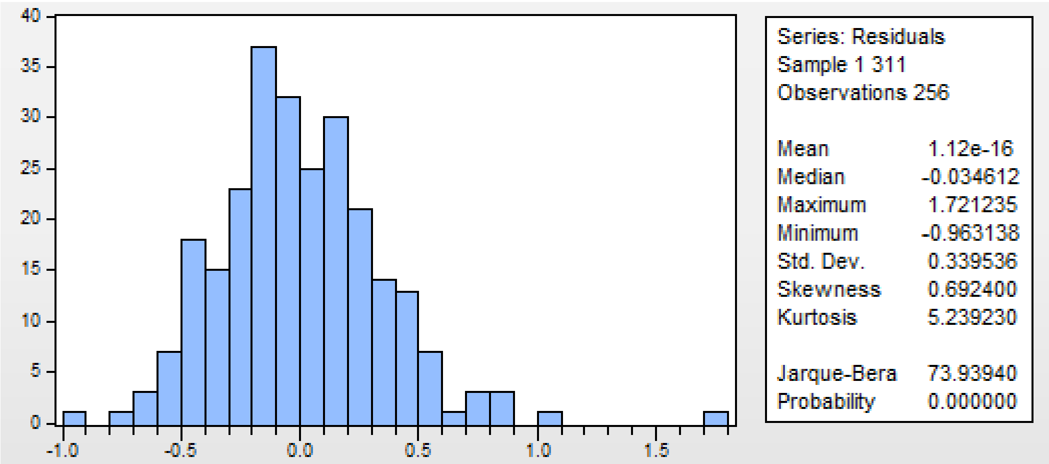
Heteroscedasticity test of OLS2 model.

Heteroskedasticity Test: White

| | | | |
|---|---|---|---|
| F-statistic | 1.303800 | Prob. F(207,48) | 0.1382 |
| Obs*R-squared | 217.3447 | Prob. Chi-Square(207) | 0.2971 |
| Scaled explained SS | 388.2056 | Prob. Chi-Square(207) | 0.0000 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/27/18 Time: 22:01
Sample: 1 311
Included observations: 256
Collinear test regressors dropped from specification

Normality test of OLS 2 model.



Multicollinearity test of OLS1

Variance Inflation Factors
Date: 10/27/18 Time: 22:06
Sample: 1 313
Included observations: 256

| Variable | Coefficient Variance | Uncentered VIF | Centered VIF |
|---|---|---|---|
| C | 0.095019 | 194.4489 | NA |
| GUESTS | 0.000337 | 15.46113 | 3.884965 |
| BATHS | 0.002180 | 10.41519 | 2.053700 |
| BEDROOMS | 0.001935 | 14.74347 | 3.827943 |
| ROOM_TYPE | 0.004208 | 6.458951 | 1.614738 |
| AIR_CONDITION | 0.002947 | 4.382359 | 1.198301 |
| BREAKFAST | 0.002992 | 1.459085 | 1.111413 |
| FAMILY_FRIENDLY | 0.003488 | 5.353440 | 1.338360 |
| CABLE_TV | 0.005072 | 1.337974 | 1.165501 |
| SMOKING | 0.002606 | 1.957992 | 1.239042 |
| DIAST_SINT | 9.95E-10 | 6.610603 | 1.398120 |
| DIST_METRO | 7.64E-09 | 5.936709 | 1.413871 |
| DENSITY | 2.72E-11 | 9.687113 | 1.571426 |
| CLEAN_FEE | 3.30E-06 | 3.899750 | 1.612672 |
| MIN_NIGHTS | 0.000356 | 3.701744 | 1.215113 |
| _24H_CHECK_IN | 0.002547 | 1.832571 | 1.188308 |
| MEMBERSHIP | 1.68E-09 | 4.423096 | 1.205416 |
| COMPANY | 0.024220 | 1.161669 | 1.134443 |
| NUM_REV | 2.55E-07 | 1.873186 | 1.238276 |
| REVIEW_SCORE | 1.01E-05 | 185.2676 | 1.166975 |
| VERIFIED_ID | 0.002261 | 2.476290 | 1.151088 |

OLS3 Model

Dependent Variable: LOGPRICE
Method: Least Squares
Date: 10/25/18 Time: 15:15
Sample (adjusted): 1 311
Included observations: 256 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.977823 | 0.307002 | 9.699680 | 0.0000 |
| GUESTS | 0.074868 | 0.018377 | 4.074095 | 0.0001 |
| BATHS | 0.274558 | 0.046645 | 5.886068 | 0.0000 |
| BEDROOMS | 0.029276 | 0.043889 | 0.667041 | 0.5054 |
| ROOM_TYPE | 0.275076 | 0.064141 | 4.288600 | 0.0000 |
| AIR_CONDITION | 0.242694 | 0.054408 | 4.460649 | 0.0000 |
| BREAKFAST | 0.084006 | 0.054780 | 1.533510 | 0.1265 |
| FAMILY_FRIENDLY | 0.106063 | 0.059195 | 1.791761 | 0.0744 |
| CABLE_TV | 0.123463 | 0.070893 | 1.741547 | 0.0829 |
| SMOKING | -0.142848 | 0.050338 | -2.837791 | 0.0049 |
| DIAST_SINT | -0.000191 | 3.06E-05 | -6.252115 | 0.0000 |
| DIST_METRO | -0.000180 | 7.94E-05 | -2.272427 | 0.0240 |
| CLEAN_FEE | 0.005031 | 0.001801 | 2.793769 | 0.0056 |
| MIN_NIGHTS | -0.033944 | 0.018742 | -1.811054 | 0.0714 |
| MEMBERSHIP | 8.66E-05 | 4.09E-05 | 2.114371 | 0.0355 |
| COMPANY | 0.302366 | 0.154848 | 1.952664 | 0.0520 |
| NUM_REV | -0.000128 | 0.000503 | -0.253838 | 0.7998 |
| REVIEW_SCORE | 0.001379 | 0.003187 | 0.432706 | 0.6656 |
| VERIFIED_ID | -0.079144 | 0.047592 | -1.662965 | 0.0976 |

| | | | |
|---|---|---|---|
| R-squared | 0.766309 | Mean dependent var | 3.956081 |
| Adjusted R-squared | 0.748560 | S.D. dependent var | 0.707092 |
| S.E. of regression | 0.354563 | Akaike info criterion | 0.835456 |
| Sum squared resid | 29.79435 | Schwarz criterion | 1.098575 |
| Log likelihood | -87.93837 | Hannan-Quinn criter. | 0.941281 |
| F-statistic | 43.17549 | Durbin-Watson stat | 2.184041 |
| Prob(F-statistic) | 0.000000 | | |

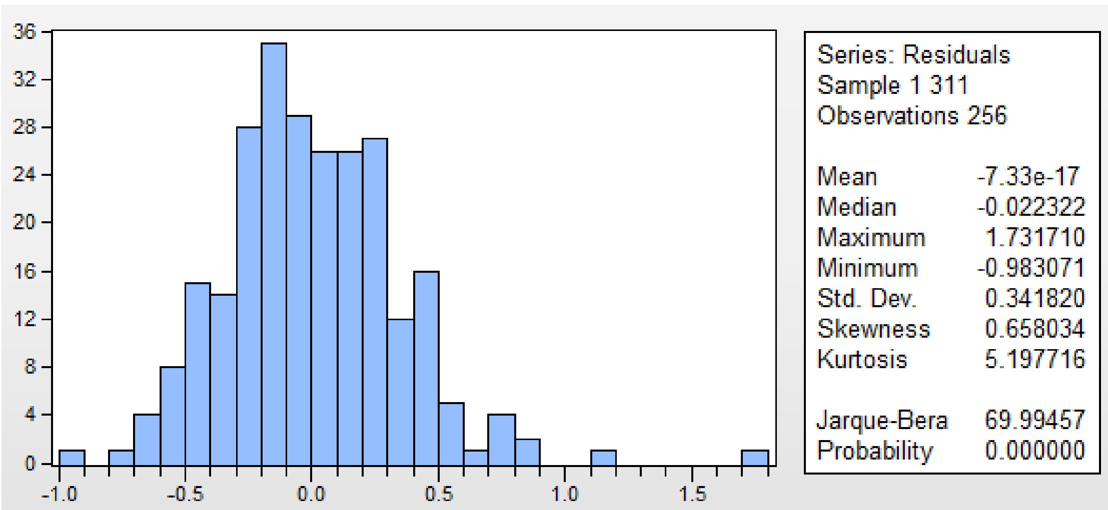
Heteroscedasticity Test of OLS3 model

Heteroskedasticity Test: White

| | | | |
|---|---|---|---|
| F-statistic | 1.045114 | Prob. F(169,86) | 0.4152 |
| Obs*R-squared | 172.1692 | Prob. Chi-Square(169) | 0.4178 |
| Scaled explained SS | 309.7100 | Prob. Chi-Square(169) | 0.0000 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/25/18 Time: 20:25
Sample: 1 311
Included observations: 256
Collinear test regressors dropped from specification

Normality test of OLS3 model



Multicollinearity test of OLS3 model

Variance Inflation Factors
Date: 10/25/18 Time: 20:31
Sample: 1 313
Included observations: 256

| Variable | Coefficient Variance | Uncentered VIF | Centered VIF |
|---|---|---|---|
| C | 0.094250 | 191.9276 | NA |
| GUESTS | 0.000338 | 15.42159 | 3.875030 |
| BATHS | 0.002176 | 10.34554 | 2.039965 |
| BEDROOMS | 0.001926 | 14.60252 | 3.791348 |
| ROOM_TYPE | 0.004114 | 6.283353 | 1.570838 |
| AIR_CONDITION | 0.002960 | 4.379736 | 1.197584 |
| BREAKFAST | 0.003001 | 1.456102 | 1.109141 |
| FAMILY_FRIENDLY | 0.003504 | 5.351546 | 1.337887 |
| CABLE_TV | 0.005026 | 1.319271 | 1.149209 |
| SMOKING | 0.002534 | 1.894663 | 1.198966 |
| DIAST_SINT | 9.34E-10 | 6.171936 | 1.305343 |
| DIST_METRO | 6.30E-09 | 4.872302 | 1.160375 |
| CLEAN_FEE | 3.24E-06 | 3.813196 | 1.576879 |
| MIN_NIGHTS | 0.000351 | 3.635330 | 1.193312 |
| MEMBERSHIP | 1.68E-09 | 4.388860 | 1.196085 |
| COMPANY | 0.023978 | 1.144396 | 1.117574 |
| NUM_REV | 2.53E-07 | 1.850802 | 1.223479 |
| REVIEW_SCORE | 1.02E-05 | 185.2349 | 1.166769 |
| VERIFIED_ID | 0.002265 | 2.468333 | 1.147389 |

OLS4 model.

Dependent Variable: LOGPRICE
Method: Least Squares
Date: 08/28/18 Time: 08:38
Sample (adjusted): 1 311
Included observations: 256 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.998220 | 0.307036 | 9.765037 | 0.0000 |
| GUESTS | 0.081544 | 0.014058 | 5.800609 | 0.0000 |
| BATHS | 0.286460 | 0.044168 | 6.485697 | 0.0000 |
| ROOM_TYPE | 0.267830 | 0.064065 | 4.180624 | 0.0000 |
| AIR_CONDITION | 0.228439 | 0.053750 | 4.250051 | 0.0000 |
| FAMILY_FRIENDLY | 0.111585 | 0.059184 | 1.885400 | 0.0606 |
| CABLE_TV | 0.133536 | 0.070694 | 1.888926 | 0.0601 |
| SMOKING | -0.142240 | 0.050365 | -2.824193 | 0.0051 |
| DIAST_SINT | -0.000188 | 3.05E-05 | -6.158149 | 0.0000 |
| DIST_METRO | -0.000175 | 7.94E-05 | -2.206295 | 0.0283 |
| CLEAN_FEE | 0.005333 | 0.001767 | 3.018979 | 0.0028 |
| MIN_NIGHTS | -0.036495 | 0.018597 | -1.962386 | 0.0509 |
| MEMBERSHIP | 8.20E-05 | 4.09E-05 | 2.003765 | 0.0462 |
| COMPANY | 0.296698 | 0.153903 | 1.927825 | 0.0551 |
| NUM_REV | -0.000203 | 0.000502 | -0.405552 | 0.6854 |
| REVIEW_SCORE | 0.001555 | 0.003183 | 0.488730 | 0.6255 |
| VERIFIED_ID | -0.085086 | 0.047392 | -1.795364 | 0.0739 |

| | | | |
|---|---|---|---|
| R-squared | 0.763644 | Mean dependent var | 3.956081 |
| Adjusted R-squared | 0.747821 | S.D. dependent var | 0.707092 |
| S.E. of regression | 0.355083 | Akaike info criterion | 0.831169 |
| Sum squared resid | 30.13409 | Schwarz criterion | 1.066591 |
| Log likelihood | -89.38966 | Hannan-Quinn criter. | 0.925855 |
| F-statistic | 48.26168 | Durbin-Watson stat | 2.237383 |
| Prob(F-statistic) | 0.000000 | | |

Heteroscedasticity test of OLS4

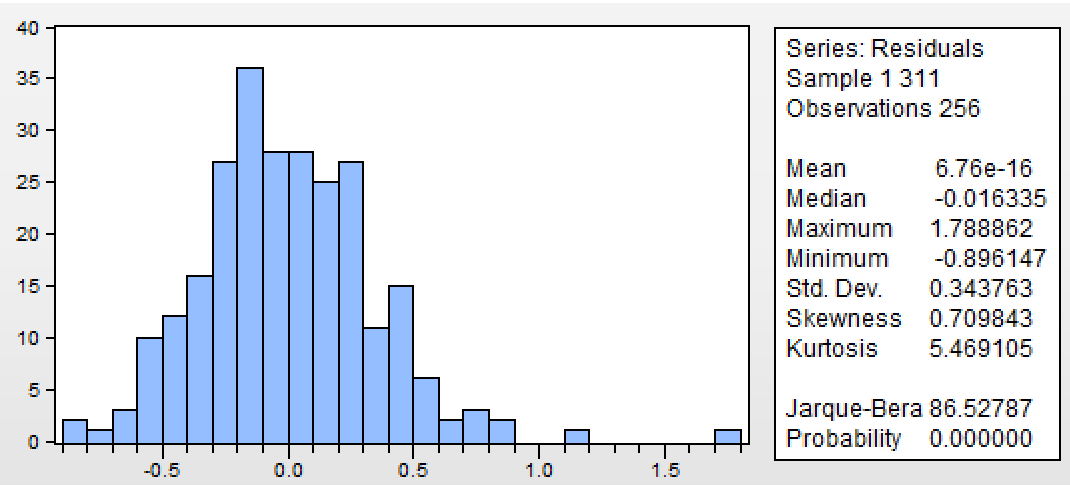
Heteroskedasticity Test: White

| | | | |
|---|---|---|---|
| F-statistic | 1.156010 | Prob. F(135,120) | 0.2088 |
| Obs*R-squared | 144.7204 | Prob. Chi-Square(135) | 0.2682 |
| Scaled explained SS | 281.8618 | Prob. Chi-Square(135) | 0.0000 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/28/18 Time: 10:44
Sample: 1 311
Included observations: 256
Collinear test regressors dropped from specification

‘

Normality test of OLS4



Multicollinearity test of OLS4

Variance Inflation Factors
Date: 08/28/18 Time: 10:46
Sample: 1 313
Included observations: 256

| Variable | Coefficient Variance | Uncentered VIF | Centered VIF |
|---|---|---|---|
| C | 0.094271 | 191.4075 | NA |
| GUESTS | 0.000198 | 8.998340 | 2.261040 |
| BATHS | 0.001951 | 9.248547 | 1.823657 |
| ROOM_TYPE | 0.004104 | 6.249979 | 1.562495 |
| AIR_CONDITION | 0.002889 | 4.261920 | 1.165369 |
| FAMILY_FRIENDLY | 0.003503 | 5.333945 | 1.333486 |
| CABLE_TV | 0.004998 | 1.308046 | 1.139430 |
| SMOKING | 0.002537 | 1.891135 | 1.196734 |
| DIAST_SINT | 9.32E-10 | 6.143971 | 1.299429 |
| DIST_METRO | 6.31E-09 | 4.861234 | 1.157739 |
| CLEAN_FEE | 3.12E-06 | 3.659020 | 1.513122 |
| MIN_NIGHTS | 0.000346 | 3.568692 | 1.171438 |
| MEMBERSHIP | 1.67E-09 | 4.366437 | 1.189975 |
| COMPANY | 0.023686 | 1.127161 | 1.100743 |
| NUM_REV | 2.52E-07 | 1.834703 | 1.212837 |
| REVIEW_SCORE | 1.01E-05 | 184.1885 | 1.160178 |
| VERIFIED_ID | 0.002246 | 2.440478 | 1.134441 |

Table 6: Descriptive statistics of variables of Study 2.

| Variable | Average | St. dev | Mean | Min | Max |
|---|---|---|---|---|---|
| Trust | 0,94333 | 0,2312 | 1 | 0 | 1 |
| Host gender | 0,4564 | 0,498 | 0 | 0 | 1 |
| Number of languages | 2,0878 | 1,077 | 2 | 1 | 7 |
| Superhost | 0,2322 | 0,4222 | 0 | 0 | 1 |
| Verified ID | 0,5032 | 0,4999 | 1 | 0 | 1 |
| Membership | 960,935 | 586,492 | 810 | 7 | 2274 |
| Review score | 94,193 | 7,616 | 96 | 40 | 100 |
| Number of reviews | 29,21 | 46,265 | 8 | 0 | 425 |

Table 7: LOGIT models

| Variable | LOGIT1 | LOGIT2 | LOGIT3 |
|---|---|---|---|
| Constant | 14.806 (1.736) * | 16.522 (2.226) ** | 12.364 (1.529) + |
| Host gender | 0.025 (0.038) [0,02536] | -0.059 (-0.089) [-0,0574478] | |
| Number of languages | 0.372 (1.247) [0,4516139] | | 0.364 (1.182) [0,440314] |
| Superhost | 1.393 (1.59) + [3,0292248] | 1.473 (1.695)* [3,3663394] | 1.129 (1.418) [2,094876] |
| Verified ID | -1.564 (-2.07) ** [-0,7907562] | -1.607 (-2.124)** [-0,1484804] | -1.321 (-1.813)* [2,747298] |
| Membership | -0.003 (-3.941) *** [-0,0030723] | -0.0031 (-4.128)*** [-0,0030962] | -0.002 (-3.821)*** [-0,002923] |
| Review score | -0.080 (-0,958) [-0,0772215] | -0.087 (-1.210) [-0,0840257] | -0.057 (-0.713) [-0,055485] |
| Number of reviews | -0.0109 (-2.042)** [-0,0108458] | -0.011 (-2.221)** [-0,0113323] | -0.0099 (-1.957) * [-0,009869] |
| | | | |
| McFadden $R^2$ | 0.3644 | 0,3511 | 0.3398 |
| AIC | 0,3958 | 0,3723 | 0,3841 |
| LR statistic | 42.11 | 41.23 | 39,86 |
| Prob. (LR statistc) | 0,0000 | 0,0000 | 0,0000 |
| N (after adjustments) | 226 | 239 | 238 |

***p<α=0,01, **p<α=0,05,*p<α=0,10, + likely to be statistically significant for a=0,10. (z – Statistics). [Odds Ratio].

Table 7 (Cont.)

| Variable | LOGIT4 | LOGIT5 | LOGIT6 |
|---|---|---|---|
| Constant | 8.024 (5.575)*** | 14.5163 (2.0548)** | 7.0355 (4.7488) *** |
| Host gender | | | 0.2115 (0.3248) [0,235602] |
| Number of languages | | | 0.3680 (1.1884) [0,444945] |
| Superhost | 0.8002 (1.1266) [1,226186] | 1.219461 (1.5671) + [2,385363] | 0.8743 (1.1398) [1,397422] |
| Verified ID | -1.2286 (-1.7256)* [-0,707308] | -1.391201 (-1.9067) *** [-0,751224] | -1.4399 (-1.9516) * [-0,763062] |
| Membership | -0.00291(-4.1146)*** [-0,002909] | -0.002975 (-3.9958)*** [-0,002971] | -0.0028 (-4.0761)*** [-0,002891] |
| Review score | | -0.069197 (-0.9910) [-0,066857] | |
| Number of reviews | -0.0112 (-2.4048)** [-0,011144] | -0.010556 (-2.1745)** [-0,010500] | -0.0117 (-2.2627) ** [-0,011713] |
| | | | |
| McFadden $R^2$ | 0.3331 | 0,3284 | 0,3687 |
| AIC | 0.3118 | 0,3663 | 0,3377 |
| LR statistic | 41.58 | 39.09 | 44,69 |
| Prob. (LR statistic) | 0,0000 | 0,0000 | 0,0000 |
| N (after adjustments) | 299 | 251 | 268 |

LOGIT1 model.

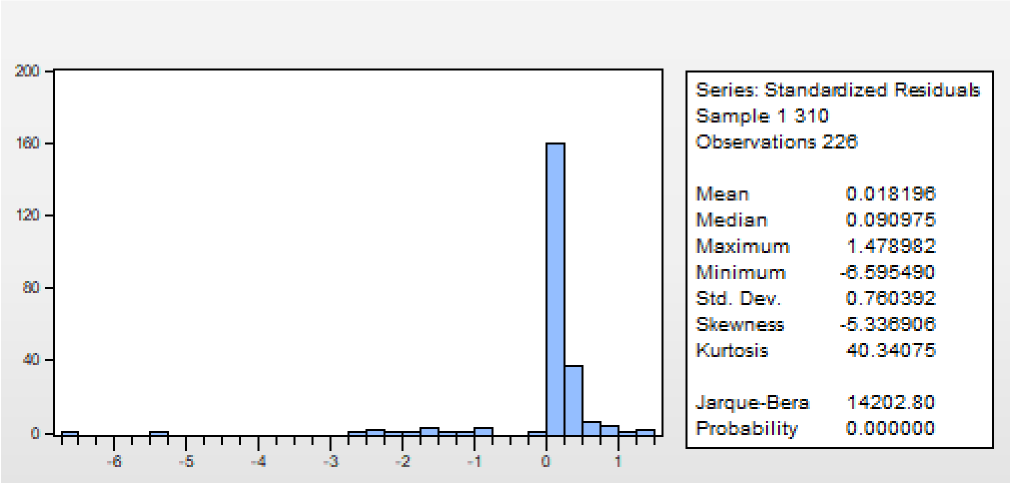
Dependent Variable: TRUST3
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/16/18 Time: 12:02
Sample (adjusted): 1 310
Included observations: 226 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 14.80648 | 8.525861 | 1.736655 | 0.0824 |
| HOST_GENDER | 0.025361 | 0.659147 | 0.038475 | 0.9693 |
| NUM_LANG | 0.372676 | 0.298698 | 1.247669 | 0.2122 |
| SUPERHOST | 1.393574 | 0.874511 | 1.593546 | 0.1110 |
| VERIFIED_ID | -1.564255 | 0.755574 | -2.070286 | 0.0384 |
| MEMBERSHIP | -0.003077 | 0.000781 | -3.941553 | 0.0001 |
| REVIEW_SCORE | -0.080366 | 0.083860 | -0.958329 | 0.3379 |
| NUM_REV | -0.010905 | 0.005340 | -2.042153 | 0.0411 |

| | | | |
|---|---|---|---|
| McFadden R-squared | 0.364415 | Mean dependent var | 0.929204 |
| S.D. dependent var | 0.257054 | S.E. of regression | 0.225144 |
| Akaike info criterion | 0.395828 | Sum squared resid | 11.05043 |
| Schwarz criterion | 0.516908 | Log likelihood | -36.72851 |
| Hannan-Quinn criter. | 0.444691 | Deviance | 73.45702 |
| Restr. deviance | 115.5738 | Restr. log likelihood | -57.78691 |
| LR statistic | 42.11680 | Avg. log likelihood | -0.162516 |
| Prob(LR statistic) | 0.000000 | | |

| | | | |
|---|---|---|---|
| Obs with Dep=0 | 16 | Total obs | 226 |
| Obs with Dep=1 | 210 | | |

Normality test of LOGIT1 model.



LOGIT 2 model.

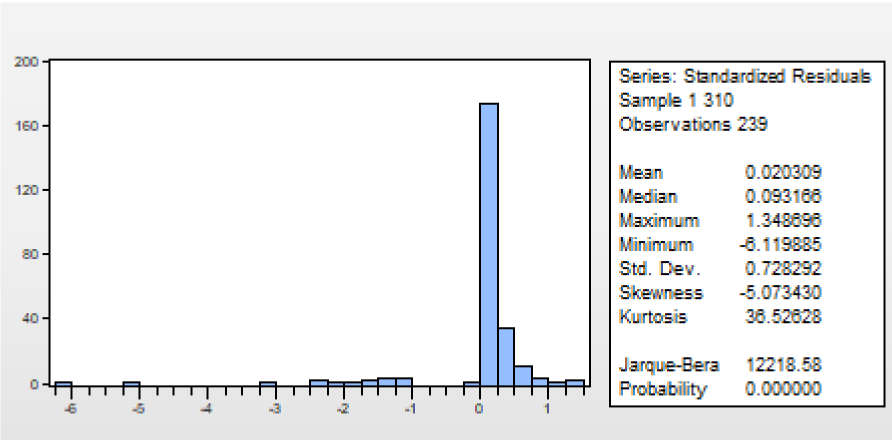
Dependent Variable: TRUST3
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/16/18 Time: 12:05
Sample (adjusted): 1 310
Included observations: 239 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 16.52203 | 7.422197 | 2.226030 | 0.0260 |
| HOST_GENDER | -0.059164 | 0.659862 | -0.089662 | 0.9286 |
| SUPERHOST | 1.473925 | 0.869544 | 1.695055 | 0.0901 |
| VERIFIED_ID | -1.607328 | 0.756661 | -2.124239 | 0.0337 |
| MEMBERSHIP | -0.003101 | 0.000751 | -4.128522 | 0.0000 |
| REVIEW_SCORE | -0.087767 | 0.072519 | -1.210251 | 0.2262 |
| NUM_REV | -0.011397 | 0.005130 | -2.221812 | 0.0263 |

| | | | |
|---|---|---|---|
| McFadden R-squared | 0.351137 | Mean dependent var | 0.933054 |
| S.D. dependent var | 0.250452 | S.E. of regression | 0.223325 |
| Akaike info criterion | 0.377384 | Sum squared resid | 11.57073 |
| Schwarz criterion | 0.479205 | Log likelihood | -38.09738 |
| Hannan-Quinn criter. | 0.418415 | Deviance | 76.19477 |
| Restr. deviance | 117.4281 | Restr. log likelihood | -58.71406 |
| LR statistic | 41.23336 | Avg. log likelihood | -0.159403 |
| Prob(LR statistic) | 0.000000 | | |

| | | | |
|---|---|---|---|
| Obs with Dep=0 | 16 | Total obs | 239 |
| Obs with Dep=1 | 223 | | |

Normality test of LOGIT2 model.



LOGIT3 model

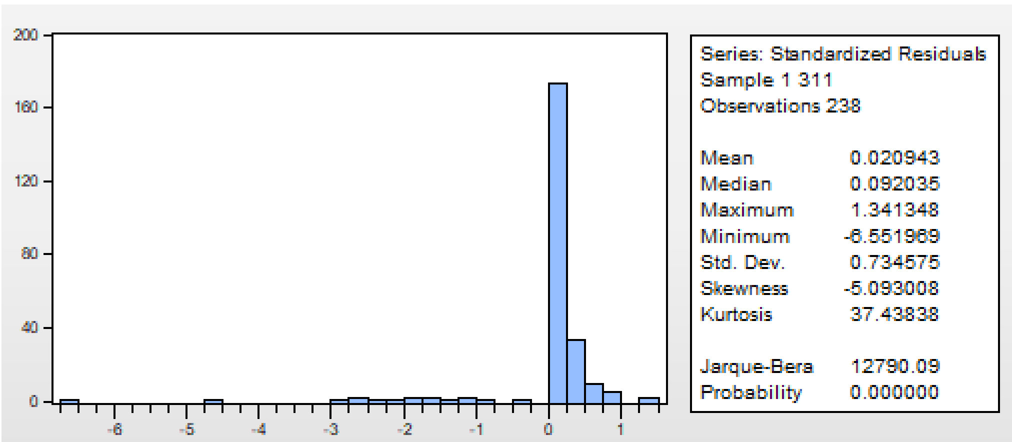
Dependent Variable: TRUST3
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/16/18 Time: 12:05
Sample (adjusted): 1 311
Included observations: 238 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 12.36456 | 8.081692 | 1.529948 | 0.1260 |
| NUM_LANG | 0.364861 | 0.308442 | 1.182919 | 0.2368 |
| SUPERHOST | 1.129748 | 0.796671 | 1.418085 | 0.1562 |
| VERIFIED_ID | -1.321035 | 0.728552 | -1.813234 | 0.0698 |
| MEMBERSHIP | -0.002927 | 0.000766 | -3.821954 | 0.0001 |
| REVIEW_SCORE | -0.057084 | 0.080008 | -0.713485 | 0.4755 |
| NUM_REV | -0.009918 | 0.005067 | -1.957363 | 0.0503 |

| | | | |
|---|---|---|---|
| McFadden R-squared | 0.339855 | Mean dependent var | 0.932773 |
| S.D. dependent var | 0.250942 | S.E. of regression | 0.225283 |
| Akaike info criterion | 0.384151 | Sum squared resid | 11.72379 |
| Schwarz criterion | 0.486276 | Log likelihood | -38.71395 |
| Hannan-Quinn criter. | 0.425309 | Deviance | 77.42790 |
| Restr. deviance | 117.2892 | Restr. log likelihood | -58.64462 |
| LR statistic | 39.86134 | Avg. log likelihood | -0.162664 |
| Prob(LR statistic) | 0.000000 | | |

| | | | |
|---|---|---|---|
| Obs with Dep=0 | 16 | Total obs | 238 |
| Obs with Dep=1 | 222 | | |

Normality test of LOGIT3 model.



LOGIT 4 model.

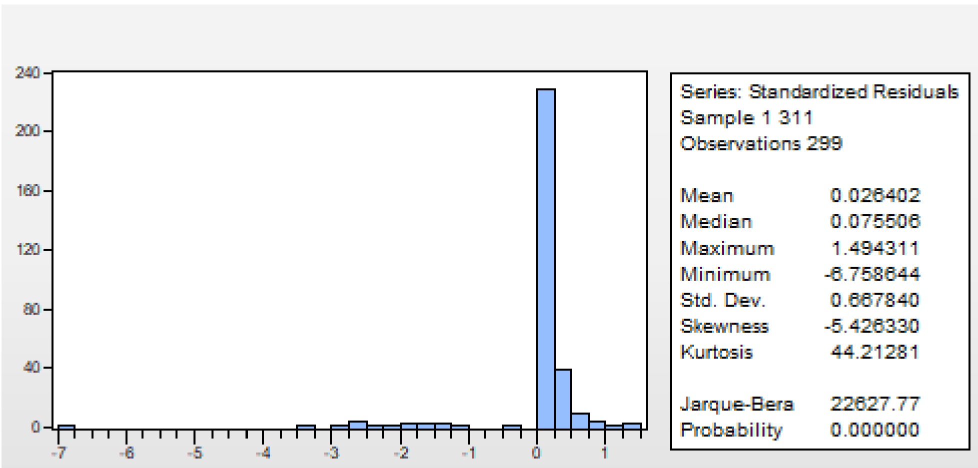
Dependent Variable: TRUST3
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/16/18 Time: 12:08
Sample (adjusted): 1 311
Included observations: 299 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 8.024034 | 1.439051 | 5.575921 | 0.0000 |
| SUPERHOST | 0.800290 | 0.710342 | 1.126627 | 0.2599 |
| VERIFIED_ID | -1.228635 | 0.711991 | -1.725633 | 0.0844 |
| MEMBERSHIP | -0.002913 | 0.000708 | -4.114670 | 0.0000 |
| NUM_REV | -0.011207 | 0.004660 | -2.404825 | 0.0162 |

| | | | |
|---|---|---|---|
| McFadden R-squared | 0.333160 | Mean dependent var | 0.946488 |
| S.D. dependent var | 0.225429 | S.E. of regression | 0.207679 |
| Akaike info criterion | 0.311821 | Sum squared resid | 12.68039 |
| Schwarz criterion | 0.373702 | Log likelihood | -41.61729 |
| Hannan-Quinn criter. | 0.336589 | Deviance | 83.23458 |
| Restr. deviance | 124.8195 | Restr. log likelihood | -62.40974 |
| LR statistic | 41.58489 | Avg. log likelihood | -0.139188 |
| Prob(LR statistic) | 0.000000 | | |

| | | | |
|---|---|---|---|
| Obs with Dep=0 | 16 | Total obs | 299 |
| Obs with Dep=1 | 283 | | |

Normality of LOGIT4 model.



LOGIT5 model.

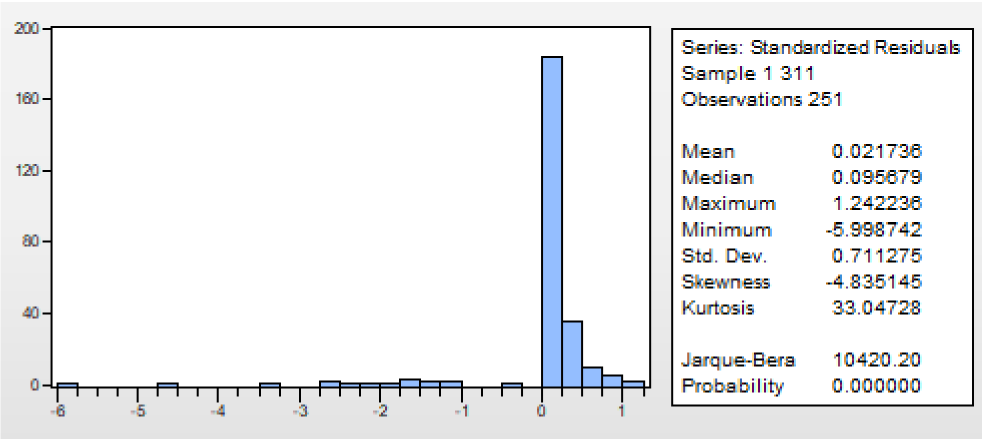
Dependent Variable: TRUST3
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/16/18 Time: 12:06
Sample (adjusted): 1 311
Included observations: 251 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 14.51639 | 7.064489 | 2.054840 | 0.0399 |
| SUPERHOST | 1.219461 | 0.778121 | 1.567188 | 0.1171 |
| VERIFIED_ID | -1.391201 | 0.729619 | -1.906751 | 0.0566 |
| MEMBERSHIP | -0.002975 | 0.000745 | -3.995825 | 0.0001 |
| REVIEW_SCORE | -0.069197 | 0.069822 | -0.991059 | 0.3217 |
| NUM_REV | -0.010556 | 0.004854 | -2.174526 | 0.0297 |

| | | | |
|---|---|---|---|
| McFadden R-squared | 0.328435 | Mean dependent var | 0.936255 |
| S.D. dependent var | 0.244786 | S.E. of regression | 0.222554 |
| Akaike info criterion | 0.366332 | Sum squared resid | 12.13496 |
| Schwarz criterion | 0.450606 | Log likelihood | -39.97470 |
| Hannan-Quinn criter. | 0.400246 | Deviance | 79.94940 |
| Restr. deviance | 119.0493 | Restr. log likelihood | -59.52467 |
| LR statistic | 39.09994 | Avg. log likelihood | -0.159262 |
| Prob(LR statistic) | 0.000000 | | |

| | | | |
|---|---|---|---|
| Obs with Dep=0 | 16 | Total obs | 251 |
| Obs with Dep=1 | 235 | | |

Normality test of LOGIT5 model.



LOGIT6 model.

Dependent Variable: TRUST3
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/16/18 Time: 12:09
Sample (adjusted): 1 310
Included observations: 268 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 7.035596 | 1.481539 | 4.748843 | 0.0000 |
| HOST_GENDER | 0.211558 | 0.651302 | 0.324824 | 0.7453 |
| NUM_LANG | 0.368071 | 0.309699 | 1.188478 | 0.2346 |
| SUPERHOST | 0.874394 | 0.767140 | 1.139810 | 0.2544 |
| VERIFIED_ID | -1.439956 | 0.737816 | -1.951647 | 0.0510 |
| MEMBERSHIP | -0.002895 | 0.000710 | -4.076157 | 0.0000 |
| NUM_REV | -0.011782 | 0.005207 | -2.262702 | 0.0237 |

| | | | |
|---|---|---|---|
| McFadden R-squared | 0.368762 | Mean dependent var | 0.940299 |
| S.D. dependent var | 0.237376 | S.E. of regression | 0.211380 |
| Akaike info criterion | 0.337742 | Sum squared resid | 11.66188 |
| Schwarz criterion | 0.431536 | Log likelihood | -38.25743 |
| Hannan-Quinn criter. | 0.375414 | Deviance | 76.51485 |
| Restr. deviance | 121.2139 | Restr. log likelihood | -60.60696 |
| LR statistic | 44.69907 | Avg. log likelihood | -0.142752 |
| Prob(LR statistic) | 0.000000 | | |

| | | | |
|---|---|---|---|
| Obs with Dep=0 | 16 | Total obs | 268 |
| Obs with Dep=1 | 252 | | |

Normality test of LOGIT6 model.