Assessing the effect of proximity to tourist attraction sites on Airbnb listings' nightly rates: Evidence from Athens, Greece

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Abstract

Motivated by the significant contribution of the tourism activity and the expansion of Airbnb listings to the Greek national and local economy in conjunction with the importance of location in Airbnb rate determination, this study investigates the impact of proximity to tourist attractions on Airbnb nightly rates in Athens. Established works find that location specifications, host-related characteristics, property features, services, and the number of reviews influence listings' nightly rates. However, the effect of proximity to attractive sites on nightly rates has been scarcely examined. By employing hedonic regression models with a cross-sectional dataset provided by Inside Airbnb, we find that, on average, listings' nightly rates increase as their distance to tourist attractions decreases, whilst controlling for other nightly rate determinants. This effect is persistent both when the independent variable is defined as the distance to the nearest tourist spot or the average distance to all tourist sites. The impact of proximity to attractive sites on nightly rates is meaningful for Airbnb owners' (price-setting) and investors' decisions, as well as for the Hellenic Government. Future research may also consider seasonal differences and nightly rate segmentation to derive more detailed findings.

Keywords: Airbnb, Nightly rates, Tourist attractions, Athens, Hedonic regression

Table of Contents

1. Introduction

Over the past few years, the enormous contribution of the tourism sector to the Greek economy has been boosted by the expansion of Airbnb and other short-term rental platforms (Gourzis et al, 2019). Importantly, increased tourism activity constitutes a vital source of income for local economies as it leads not only to an upward shift in established companies' profits but most importantly to an expansion of real estate developments, local business activity and labour demand (Ikkos & Koutsos, 2020). Moreover, it is important to note that the Greek economy has been ranked as the sixth most tourism-dependent economy of the thirty-five OECD members in 2016 (Bellos, 2019). A critical factor influencing the high level of tourism activity and its described effects on the Greek economy has been the expansion of Airbnb; an online platform that offers short-term accommodation (Skoultsos et al, 2020). Airbnb was founded in 2007 and it currently consists of almost 3 million hosts who have been offering accommodation to more than 1 billion guests in 220 countries (Airbnb, 2022). The major advantage of Airbnb listings compared to other forms of hospitality is that they provide the guests with a cheaper, more convenient, and unique experience (Nieuwland & Melik, 2020). Moreover, Alyakoob & Rahman (2018) notice that in some neighbourhoods of New York City, a 2.5% rise in Airbnb reviews is associated with a 3.8% increase in employment of local restaurants, indicating thus the contribution of Airbnb to the local economy. Observing the wider effects of tourism activity in Greece, the Institute of the Association of Greek Tourism Enterprises notes that direct and indirect economic activity arising from tourism represented at least 25.7% of the country's Gross Domestic Product (GDP) in 2018, whilst between 36.7% and 44.2% of the total Greek workforce was employed in tourism-related corporations (Bellos, 2019). Whilst facilitating greater tourism activity, Airbnb is also considered a valuable tool for investors to make profits by buying properties and offering them as a short-term rental (STR) on the platform (Nieuwland & Melik, 2018). Evidently, Airbnb is influential both towards investment decisions and the wider economy. The aforementioned positive socio-economic effects of Airbnb on the city of Athens are discussed in the works of Gourzis et al. (2020), Skoultsos et al. (2020) and Balampanidis et al. (2021).

Additionally, the majority of scientific research underlines that location constitutes a crucial factor in Airbnb listings' price determination (Wang & Nicolau, 2017). According to Gutierrez et al. (2017), tourists seek to find accommodation in proximity to tourist attractions, whilst Kranioti et al. (2022) support that Athens is a metropolitan city with a great cultural and archaeological heritage. One must consider that Airbnb listings may be located near tourist attractions since many of these properties might have already been constructed before the emergence of planning constraints (Gourzis et al, 2019; Gutierrez et al., 2017). This locational advantage is deemed as the major argument as to why the demand for Airbnbs has been rapidly growing over the years (Gourzis et al., 2019). Therefore, acknowledging this locational advantage of Airbnb listings in conjunction with the significant contribution of Airbnb to the Greek economy (Bellos, 2019), it could be meaningful to investigate how proximity to tourist attractions impacts Airbnb listings' nightly rates.

Only a limited number of studies have already examined the effect of proximity to tourist attraction sites on nightly rates. More specifically, Chang & Li (2021) note that a 1-km increase in distance to attractive spots is related to 3.1% lower nightly rates in Beijing, Shanghai, and Guangzhou whilst Wang & Rasouli (2022) also note a negative association between km-distance to attractive sites and nightly rates in Amsterdam. The authors (2022) find that a 1% increase in km-distance to tourist spots is linked with an approximately 0.16% decrease in nightly rates. Similarly, Perez-Sanchez et al. (2018) find that Airbnbs located within specified tourist attractive areas demonstrate 16% higher nightly rates compared to listings that are situated outside of these areas, in four Spanish cities.

The focus of this thesis is to identify the pure effect of proximity to tourist attractions on nightly rates and it is thus essential to understand other nightly rate determinants. Cited works indicate several factors influencing Airbnb listings' nightly rates. More specifically, Wang & Nicolau (2017), find that the factors affecting Airbnb nightly rates can be classified into Host Attributes (e.g. Superhost, Host listing count), Site & Property Attributes (e.g., distance from the city centre, room type, guests' capacity), Amenities & Services (e.g. free parking, wireless internet), Rental Rules (e.g. cancellation policy) and Online Reviews (e.g. reviews per year). Low & Luth (2021) also incorporate binary variables for each different city used in the dataset. Previous studies have also examined the impact of Airbnbs' location on nightly rates in terms of distance to the city centre (Wang & Nicolau, 2017; Gibbs et al., 2017; Low & Luth, 2021). Specifically, cited works find that Airbnb prices decrease as proximity to the centre increases.

Overall, the impact of various rate determinants such as internal amenities and service attributes on nightly rates has been widely examined (Wang & Nicolau, 2017; Gibbs et al., 2017; Chang & Li, 2021; Low & Luth, 2021). However, we observe that the effect of external amenities in terms of distance to tourist attractions on listings' rates has been scarcely investigated, based on a wide variety of established literature examining the Airbnb listings' price determination searched online in several journals such as the "Journal of Tourism Management" and the "International Journal of Hospitality Management". In fact, as aforementioned, we only found three works examining this effect in Amsterdam (Wang & Rasouli, 2022), 3 Chinese cities (Chang & Li, 2021) and 4 Spanish cities (Perez-Sanchez et al., 2018). Evidently, location specifications have a significant impact on demand for Airbnb listings since cited works observe a significant and major effect of proximity to tourist attractions on Airbnb's nightly rates (Wang & Rasouli, 2022; Chang & Li, 2021; Perez-Sanchez et al., 2018). As Wang & Nicolau (2017) note, although it is well acknowledged that location plays an important role in the price determination of Airbnb listings, the various location attributes that have an influence on nightly rates are not yet entirely defined. Moreover, established literature examining the effect of proximity to tourist attractions on nightly rates, such as the works of Wang & Rasouli (2022) and Chang & Li (2021), only consider the nearest distance to tourist attractions. In contrast with cited works and acknowledging that tourists might prefer to be accommodated in proximity to several attractions rather than only one, this thesis aims at examining the influence of proximity to tourist attractions, using two different definitions, the distance to the nearest tourist attraction and the average distance to all tourist attractions. Moreover, it must be noted that this effect varies in magnitude across different cities. For instance, Chang & Li (2021) find that a unitary increase in km-distance to the nearest tourist attraction is associated with a 3.1% decrease in nightly rates in 3 Chinese cities whilst Wang & Rasouli (2022) find that a 1% increase in km-distance to attractive sites is related to an 0.16% decrease in nightly rates. Therefore, given the significant variation in the magnitude of this effect on nightly rates found in cited studies, we believe that the findings of these works cannot be generalized to Athens. This could be attributed to the heterogeneity existing in the real estate market (Low & Luth, 2021). Agreeing with this statement, Perez-Sanchez et al. (2018) note that the findings of empirical models using the OLS techniques are certain only for the work's study area and cannot be generalized. Therefore, since the findings of the limited amount of scientific research that has investigated the effect of proximity to tourist attractions on nightly rates may not be generalized as explained above, examining the influence of this factor on Airbnb listings' nightly rates in Athens can yield a meaningful contribution. Therefore, the research aim of this thesis can be formulated into the following research question:

How do Airbnb rates vary with proximity to the Athenian tourist attraction sites?

This study contributes to the academic literature by examining the impact of location attributes on Airbnb listings' nightly rates. More precisely, we investigate the effect of proximity to tourist attractions on nightly rates under two different definitions with the first being the distance to the nearest tourist attraction and the second being the average distance to all tourist attractions. This second definition considers the probable preference of visitors to be accommodated in proximity to several attractions rather than just one. To the best of our knowledge, this parameter has never been accounted for in established studies. Moreover, the findings of this work could be meaningful for future studies, since they may be compared to the results of other works examining the effect of proximity to tourist attractions on nightly rates, such as the studies of Wang & Rasouli (2022) and Chang & Li (2021). Essentially, this may contribute to understanding the reasoning behind variations in the magnitudes of this effect found across different cities. For instance, by comparing different case studies one could find that these variations might occur because of well-connected and more accessible public transportation that can decrease visitors' willingness to pay to be accommodated in proximity to attractive sites.

Additionally, the findings of this study may be meaningful for investors interested in short-term rentals, by demonstrating the importance of location towards nightly rates. More precisely, an anticipated increase in nightly rates after an increase in proximity to attraction sites reflects a higher level of income stream generated from a property. Moreover, in case a positive and significant effect is found by the increase in proximity to tourist attractions on Airbnb nightly rates, the Government might aspire to stimulate additional tourist attractions in areas lacking such sites. In this way, an increasing amount of Airbnb listings might emerge in these areas, and thus a greater level of tourist expenditures toward local businesses may be anticipated (Alyakoob & Rahman, 2018). This is aligned with higher tax revenues for the government, an expanded multiplier effect in the economy and thus greater GDP in the long term.

To assist the aim of this study, a dataset consisting of Airbnb listings' cross-sectional observations in Athens is provided by Inside Airbnb. Next to this, the ten most visited tourist attraction sites are selected from tripadvisor.com, as in the work of Wang & Rasouli (2022). With the assistance of the geographical information system (GIS), the specified area of this research is identified and distances from Airbnb listings to the tourist attractions and metro stations are estimated. In addition, hedonic regression models are employed to isolate and identify the influence of proximity to tourist attraction sites on Airbnb nightly rates.

The remainder of this paper is structured as follows: Section 2 focuses on established literature concerning nightly rate determinants, focusing on the importance of locational attributes. Section 3 provides an explanatory analysis of the rate-determining variables chosen from the dataset and describes the employed hedonic regression models. Section 4 exhibits the empirical results. Lastly, section 5 provides a discussion regarding how the results could act as signals for real estate investors and the Hellenic government. Further, concluding remarks and suggestions for further research are noted.

2. Literature Review

2.1 Locational determinants of Airbnb nightly rates

As mentioned, Airbnb pricing is very important for real estate investors, hosts, as well as the wider local economy (Nieuwland & Melik, 2018; Alyakoob & Rahman, 2018; Gourzis et al, 2019) and given the aforementioned locational advantage of Airbnb listings, it is of great importance to investigate how proximity to tourist attraction sites affects Airbnb listings' nightly rates. Cited works provide important findings regarding this effect, along with the influence of other price determinants on Airbnb rates. First, the work of Wang & Nicolau (2017) aims at detecting the factors affecting listings rates in 33 cities across the globe using a sample of 180.533 Airbnb listings provided by Insideairbnb.com. In their OLS analysis, the writers (2017) find that almost every variable used, classified into five categories - Host, Property, Services, Rental Rules, and Reviews -, significantly affects listings' rates while all independent variables are good predictors in their Quantile Regression analysis. Precisely, Wang & Nicolau (2017) note that host attributes (superhost status and host listings count), property attributes (number of bathrooms, bedrooms, and accommodated guests) as well as the majority of the internal amenities provided (real bed, wireless internet, free parking) and the rating of the listings are on average positively correlated with nightly rates. In contrast, listings located at a greater distance from the city centre and the ones receiving more reviews per year are associated with lower nightly rates (Wang & Nicolau, 2017). Therefore, their study (2017) contributes to established literature by identifying the determinants of Airbnb rates but also by providing their impact on different rate levels (QR analysis). Similarly, the study of Gibbs et al. (2017) identifies the effect of various listing characteristics on Airbnb's nightly rates in five Canadian metropolitan cities (Montreal, Calgary, Toronto, Ottawa, and Vancouver) by employing hedonic models with a sample of 15.716 scrapped active listings. To sum up, the writers (2017) find that host characteristics (such as the superhost status and whether the host is a professional), property characteristics (number of bathrooms, bedrooms, and accommodated guests), listings' proximity to the central business district (CBD), and provided services (parking space, pool, and gym) have a positive impact on nightly rates whilst the more the number of a listing's reviews the lower the rate will be, on average. Their models explain at least 50% of the variance of nightly rates and thus offer substantial information to Airbnb owners. Additionally, Low & Luth (2021) examine the effect of price-determining factors on Airbnb rates in seven major German cities (Berlin, Munich, Hamburg, Cologne, Dresden, Stuttgart, and Frankfurt) in order to identify the importance of quality signals in Airbnb's trust-building mechanisms. With the assistance of a web scraper, the writers (2021) collect 18.052 initial observations to carry out hedonic models. Low & Luth (2021) conclude that high-rated listings, which is a clear indication of trustworthy hosts, as well as the time length for which a host has been registered on the platform are positively correlated with nightly rates. Moreover, Chang & Li (2021) aim at identifying several variables' as well as their interacted effects on listings rates in three Chinese cities (Beijing, Shanghai, and Guangzhou). The dataset is scrapped from Airbnb.com and consists of 65.130 observations, that are incorporated into OLS regression models after data cleaning. The results indicate that the effect of room type, the city where the listing is located and the distance to tourist attractions on nightly rates have the greatest magnitude (Chang & Li, 2021). In addition, Perez-Sanchez et al. (2018) aiming at identifying the influence of more listings' rates determinants, employ hedonic regression models to mainly examine the impact of location characteristics on Airbnb pricing in four Spanish cities (Valencia, Alicante, Elche, and Plana). The data used was provided by AirDNA and their sample consists of 19,578 observations. Their findings suggest that, in both OLS and quantile regression models, listings that are located within sightseeing areas are related to greater nightly rates compared to listings that are located further away. Moreover, Perez-Sanchez et al. (2018) indicate that physical attributes, user perception as well as other location characteristics such as distance to the coastline, also have a significant impact on nightly rates. Lastly, Wang & Rasouli (2022) investigate the effect of streetscape characteristics on Airbnb listings' nightly rates in Amsterdam. Their dataset was provided by Inside Airbnb and consists of two subsamples retrieved on the 9th of July and on the 3rd of November 2020, with a final sample of 24,150 observations. To assess the purpose of their research, they use 3 proxies of streetscape design which are greenery, enclosure, and walkability and by employing hedonic models based on geographically weighted regression they find that greenery and enclosure positively impact nightly rates whilst walkability has a negative effect on nightly rates.

Regarding the influence of proximity to attractive sites on nightly rates found in cited works, Chang & Li (2021) note that an increase in distance to attractive sites (in km) is associated with a 3.1% decrease in listings rates in three major Chinese cities. Similarly, Wang & Rasouli (2022), also note a positive relationship between proximity to tourist attractions and nightly rates in Amsterdam, finding that the effect of a 1% increase in km-distance to tourist spots is linked to approximately 15% lower nightly rates. It is also worth mentioning that Wang & Rasouli (2022) only include one tourist attraction in the city of Amsterdam, the Rijksmuseum. This might lead to insufficient results given that other tourist spots that could have an impact on nightly rates are not considered in their research. Likewise, Perez-Sanchez et al. (2018) find that listings situated within the identified tourist attraction area demonstrate 16% greater nightly rates compared to listings that are not located in the same area, in four Spanish cities, by examining the impact of proximity to tourist attractions with the assistance of heatmaps from instasight.com. Their work thus only indicates price differentials between listings located inside and outside of the specified attractive area and does not reveal the effect of a 1 km change in distance to tourist sites on nightly rates. Therefore, although scarcely investigated, it is evident that proximity to tourist attractions is a major determinant of Airbnb listings' nightly rates.

Generally, location characteristics other than proximity to touristic sites are well examined by established literature. In fact, Wang & Nicolau (2017), Gibbs et al. (2017), and Low & Luth (2021) observe a negative relationship between distance to the city centre and nightly rates. Low & Luth (2021) also note that the direction of the effect of proximity to the CBD on nightly rates could be altered as distance exceeds a specific threshold. More specifically, the authors (2021) find that the effect of proximity to the centre on nightly rates in the seven German cities examined in their work changes from positive to negative at a point between 10 to 15 kilometres. Moreover, Chang & Li (2021) and Low & Luth, (2021) also take into account locational effects by segregating their study area into cities or regions whilst investigating the determinants of listings' rates. Wang & Rasouli (2022) find a negative relationship between the distance of a listing to the central station and nightly rates. However, Chang & Li (2021) observe that distance to the subway is positively correlated with rates while the effect of proximity to the railway station is insignificant. As the writers (2021) argue, this contradiction arises because the vast majority of subways and railway stations in the three Chinese cities investigated are commonly located in close proximity to the CBD, where the quality of life is relatively low due to a high rate of criminality. Nevertheless, the writers (2021) note that as the distance to the airport increases, listings' nightly rates decline. Therefore, it is evident that location plays a vital role in the pricing of Airbnb listings whilst the vast majority of literature finds a negative association of listings' proximity to public transport or the CBD with nightly rates (Wang & Nicolau, 2017; Gibbs et al., 2017; Low & Luth, 2021; Chang & Li, 2021). Since most of the identified price determinants (CBD proximity, airport proximity, public transport proximity) exhibit a negative association of distance from listings with nightly rates, this further strengthens the argument that the proximity of listings to tourist attraction sites may have a positive association with Airbnb nightly rates.

2.2 Non-locational determinants of nightly rates

Next to the locational factors discussed above, established literature has also examined the effect of other parameters on Airbnb listings' nightly rates. Comparing the findings of cited works could provide a more insightful indication regarding the impact of non-locational factors on Airbnb rates. According to Wang & Nicolau (2017), hosts that have rented their listings at least 10 times preserve at least a 90% response rate, have been 5-star reviewed at least 80% of the times booked, and have not cancelled any of their bookings, tend to obtain a superhost status. This status classification is on average associated with higher nightly rates (Wang & Nicolau, 2017; Gibbs et al., 2017; Chang & Li, 2021). Furthermore, nightly rates increase with the number of listings provided by a host according to Wang & Nicolau (2017) whilst being a professional host is also associated with higher rates (Gibbs et al., 2017). Entire homes and apartments exhibit higher pricing compared to private and shared rooms whilst private rooms are also related to higher prices in comparison to shared ones, ceteris paribus (Wang & Nicolau, 2017; Gibbs et al., 2017; Low & Luth, 2021; Chang & Li, 2021). Moreover, the number of bedrooms and guests' capacity are both positively correlated with nightly rates (Wang & Nicolau, 2017; Gibbs et al., 2017; Low & Luth, 2021). Regarding the services offered to guests, the provision of real beds (rather than sofa beds or airbeds) (Wang & Nicolau, 2017; Low & Luth, 2021), as well as wireless internet connection (Wang & Nicolau, 2017) demonstrate a positive association with nightly rates. Additionally, Wang & Nicolau (2017) find that breakfast provision is negatively correlated while free parking is positively correlated with nightly rates. In addition, regarding the effect of booking rules, Wang & Nicolau (2017) and Chang & Li (2021) find that a moderate or strict cancellation policy is related to higher Airbnb nightly rates. Lastly, an increase in listings' total reviews or reviews per year relates to a decline in Airbnb nightly rates, whilst higher ratings are associated with greater rates (Wang & Nicolau, 2017; Gibbs et al., 2017; Low & Luth, 2021; Chang & Li, 2021).

Therefore, based on established literature, we derive the conceptual model of this work which considers the dependent variable (nightly rates) as a function of proximity to tourist attractions which is the key independent variable of this work and several control variables that can be classified as host-related characteristics, property features, services, number of reviews and other location specifications.

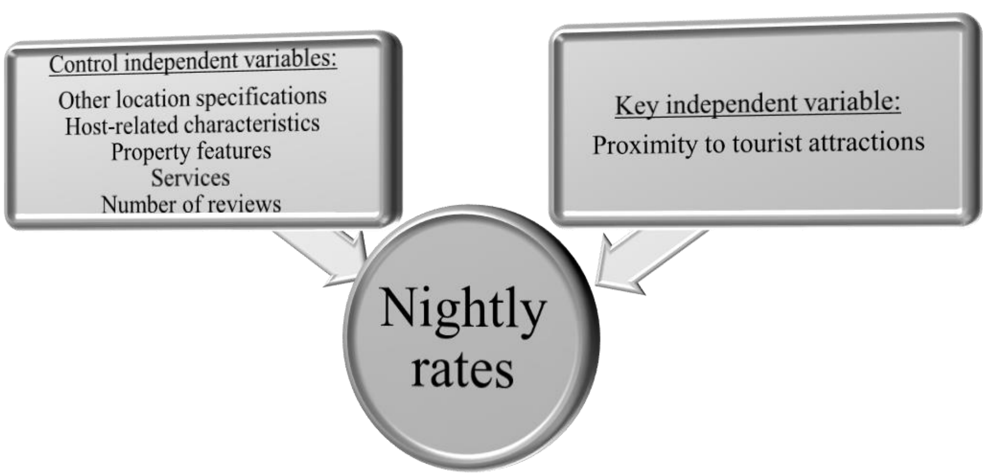

Figure 1. Conceptual Model

Overall, established literature has widely recognized the importance of location attributes on the pricing of Airbnb listings, but has not sufficiently examined the impact of proximity to tourist attractions on nightly rates. Based on the findings of Chang & Li (2021), Wang & Rasouli (2022) and Perez-Sanchez et al. (2018), we expect that Airbnb listings in close proximity to the Athenian tourist attractions will have, on average, higher nightly rates. This is also supported by the fact that Airbnb listings are situated nearby archaeological and attractive sites (Balampanidis et al., 2021) in Athens, a city with a great cultural and archaeological heritage (Kranioti et al., 2022). Therefore, the following hypothesis is being formulated and will be tested in this work:

***Hypothesis**: Proximity to tourist attraction sites is positively and significantly associated with Airbnb nightly rates, in Athens.*

3. Data & Methodology

3.1 Study Area

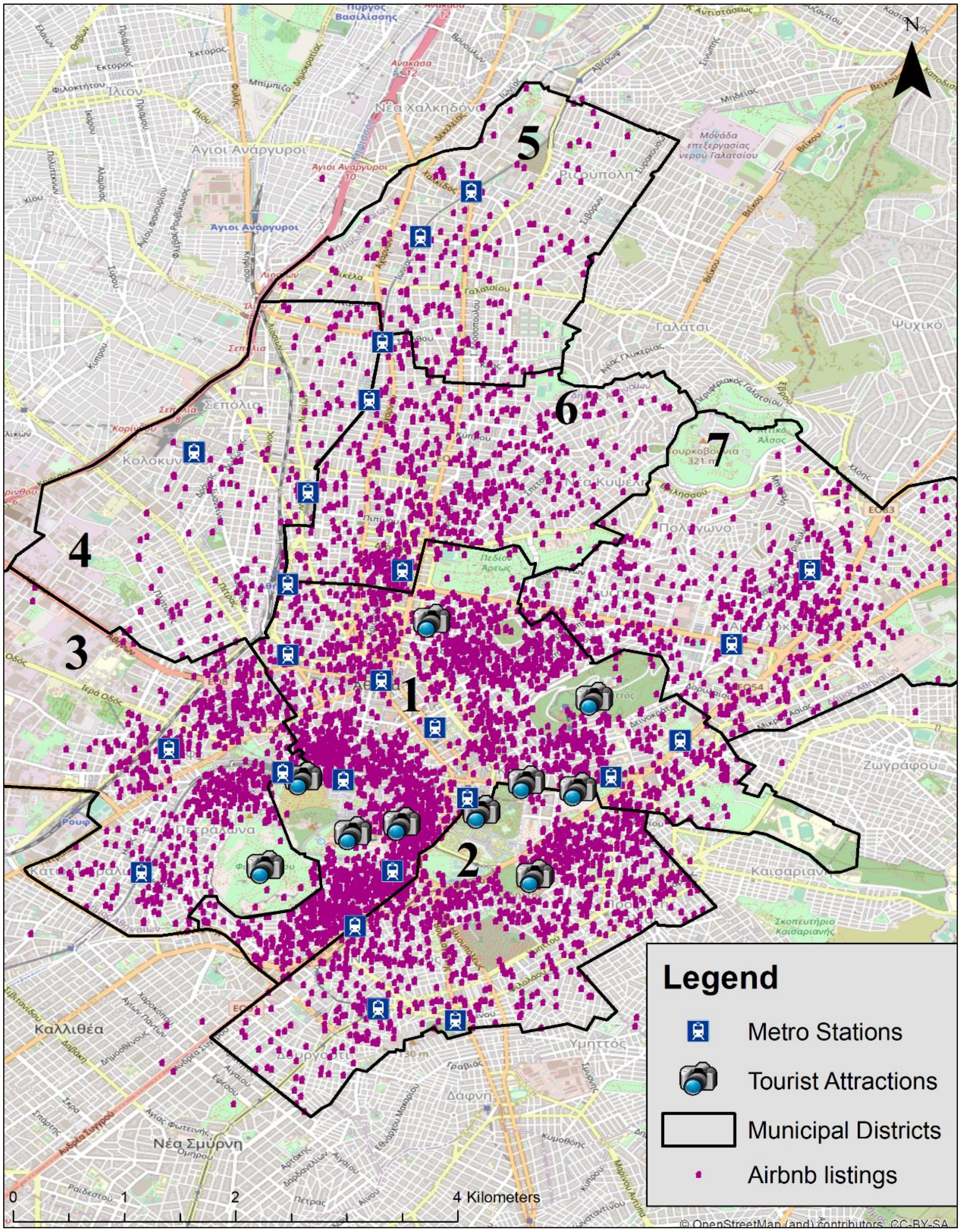

Figure 2. Spatial distribution of Airbnb listings across Athens' municipal districts in conjunction with tourist attractions and metro stations. Data regarding the Airbnb listings were provided by Inside Airbnb, the Tourist Attractions by Tripadvisor, whilst for Metro Stations and the Municipal Districts by the Hellenic Government.

Athens is the capital of Greece. It has more than 3 million residents and it is the most densely populated city in Greece (Gourzis et al., 2019). It is a European metropolitan city with extraordinary cultural and archaeological sites as well as well-known museums (Kranioti et al., 2022). The number of international air arrivals in Athens exceeded 3.700.000 in 2021 while the number of visitors travelling by airplane surpassed 6.400.000 before the occurrence of the COVID-19 pandemic in 2019 (Statista, 2022). Kranioti et al. (2022) note that "the historic centre of Athens acts as a pole for visitors" and as demonstrated in Figure 2, it is evident that the majority of the 5127 Airbnb listings in Athens are situated nearby tourist attractive sites.

According to the Hellenic Statistical Authority – ELSTAT (2022), 1.021.057 tourists visited museums in Athens in 2021 with the most popular being the Acropolis Museum (more than 500.000 visitors). The National Archeological Museum and the Benaki Museum attracted almost 135.000 and 80.000 visitors respectively in 2021 (ELSTAT, 2022). It must be noted that due to the pandemic of COVID-19, the Hellenic government implemented measures such as the closure of museums from the beginning of 2021 until May 2021. Thus, observing museum visits in 2019 rather than in 2021 may provide a more representative indication of the tourist footfall in Greek museums. In total, more than 2.700.000 guests visited museums in Athens and almost 1.900.000 tourists travelled to archaeological sites with Acropolis being the most popular one (1.219.717 visitors) in 2021. In 2019 archaeological sites were visited by more than 6.000.000 guests with almost 3.600.000 of them going to Acropolis (ELSTAT, 2022).

3.2 Methodology

Hedonic regression models are employed to test the hypothesis of this thesis, which entails that the distance of Airbnb listings to tourist attraction sites has a significant negative effect on nightly rates. The hedonic modelling controls for the influence of specific nightly rate determinants and thus isolates the impact of proximity to tourist attractions on the dependent variable – nightly rates. The empirical methods used include the application of the ordinary least square (OLS) technique. The OLS assumptions have been tested and noted at length in Appendix B.

The dependent variable (Y) is the listings' nightly rate. This variable can be explained by a set of attributes. More precisely, the independent variables used in this work are classified as location specifications (L), host-related characteristics (H), property features (P), services (S), and the number of reviews (R). Therefore, the dependent variable can be described as a function of these 5 classifications and the following theoretical hedonic model is formulated:

$$\text{Nightly rate} = f\,(L, H, P, S, R) \qquad (0)$$

Based on most of the cited works (Wang & Nicolau, 2017; Gibbs et al., 2017; Chang & Li, 2021; Low & Luth, 2021) several control independent variables will be included to serve the purpose of this thesis. However, given that this work aims to measure the impact of proximity to tourist attractions on Airbnb nightly rates, not all existing variables in the dataset will be incorporated. For the category of host-related characteristics, the variables Superhost, Host Listing Count and Cancellation Policy will be selected. Regarding the property features, variables for the number of Bedrooms, Bathrooms and Guests Capacity will be used whilst a categorical variable will account for different Room Types (entire home/apartment, private room, and shared room). For the services classification, the provision of Real Beds, Breakfast, Free Parking Space, Wireless Internet, and a Pool will be indicated through a generated binary variable for each internal amenity. In addition, considering the review classification, the Average number of Reviews per Month will be incorporated. Moreover, to measure the pure effect of proximity to tourist attractions and to avoid omitted variable bias, a variable that accounts for the impact of Distance to the nearest metro station on listings' nightly rates will also be included. Lastly, inspired by the work of Low & Luth (2021) spatial differences across Municipal Districts in the city of Athens will also be considered in the analysis using binary variables for each district (Table 2). The distribution of Airbnb listings across Athens' municipal districts is demonstrated in Figure 3 while Table 2 provides the definition and the description of the variables used.

Since the distribution of the dependent variable (nightly rates) is skewed to the right (Appendix C), this variable is transformed into its natural logarithm to become normally distributed, in accordance with the hedonic modelling conditions. Moreover, due to the presence of heteroscedasticity, robust standard errors are used in all of this thesis' models. Consequently, we can derive the first empirical model of this thesis.

$$\begin{gathered}\text{Ln(Nightly rates)} = \beta_0 + \boldsymbol{\beta_1}\text{ (Proximity to tourist attractions (km))} + \beta_2\text{ (Distance to nearest metro}\\ \text{station)} + \beta_3\text{ (Superhost)} + \beta_4\text{ (Hosts' listings count)} + \beta_5\text{ (Cancellation policy)}\\ + \beta_6\text{ (Room type)} + \beta_7\text{ (Guests Capacity)} + \beta_8\text{ (No. Bedrooms)} + \beta_9\text{ (No. Bathrooms)}\\ + \beta_{10}\text{ (Pool)} + \beta_{11}\text{ (Real bed)} + \beta_{12}\text{ (Breakfast)} + \beta_{13}\text{ (Free parking space)} + \beta_{14}\text{ (Wi-Fi)}\\ + \beta_{15}\text{ (Reviews/month)} + \beta_{16}\text{ (Municipal Districts)} + \varepsilon\\ (1)\end{gathered}$$

The dependent variable is the natural logarithm of nightly rates. β_0 indicates the constant, β_{1-15} are the coefficients of the independent variables used whilst ε represents the error term. The coefficient of the key-independent variable is $\boldsymbol{\beta_1}$ which captures the direction and magnitude of the influence of listings' proximity to tourist attractions on nightly rates. Two definitions of this effect are considered with the first being the distance to the nearest tourist attraction. However, acknowledging that tourists might prefer to be accommodated in proximity to various tourist attractions rather than being located at a close distance from one specific site, we alter the definition of proximity to tourist attractions from distance to the nearest tourist attraction to the average distance to all tourist attractions.

Lastly, we observe a slight deviation from a linear relationship between proximity to tourist attractions and nightly rates, as demonstrated in Figures 4a & 4b. Therefore, to further examine the robustness of the effect of proximity to tourist attractions in model 1, the measurement of the key independent variable is altered in model 2. In this second empirical model, the independent variable of interest becomes a categorical variable reflecting the listings' proximity to tourist attractions. Again, we use two definitions of this key independent variable, the distance to the nearest tourist attraction site and the average distance to sites.

$$\begin{gathered}\text{Ln(Nightly rates)} = \beta_0 + \boldsymbol{\beta_1} \text{ (Proximity to tourist attractions (categorical))} + \beta_2 \text{ (Distance to} \\ \text{nearest metro station)} + \beta_3 \text{ (Superhost)} + \beta_4 \text{ (Hosts' listings count)} + \beta_5 \text{ (Cancellation policy)} \\ + \beta_6 \text{ (Room type)} + \beta_7 \text{ (Guests Capacity)} + \beta_8 \text{ (No. Bedrooms)} + \beta_9 \text{ (No. Bathrooms)} \\ + \beta_{10} \text{ (Pool)} + \beta_{11} \text{ (Real bed)} + \beta_{12} \text{ (Breakfast)} + \beta_{13} \text{ (Free parking space)} + \beta_{14}\text{(Wi-Fi)} \\ + \beta_{15} \text{ (Reviews /month)} + \beta_{16} \text{ (Municipal Districts)} + \varepsilon \\ (2)\end{gathered}$$

Therefore, the focus of this thesis, which is the proximity to tourist attractions, is measured in 4 different ways whilst their effect on nightly rates is always represented by the coefficient β1. First, in Model 1, the key independent variable is continuous and indicates the distance of listings to the nearest tourist attraction. Secondly, we observe that the relationship between proximity to the nearest tourist attraction and nightly rates is not linear per se, as demonstrated by Figure 4a. Therefore, the distance of listings to tourist attractions is split into categories in Model 2. The distance classifications of this key variable will be 0 – 0.25 km; 0.25 – 0.5 km; 0.5 – 0.75 km; 0.75 – 1 km; 1 – 1.5 km; 1.5 – 2 km and more than 2 km. Thirdly, since visitors might have a preference to book a listing in proximity to several attractions rather than only one we alter the definition of proximity to tourist attractions from the distance to the nearest tourist spot to the average distance to all attractive sites in Model 1* and Model 2*. Again, this definition is measured in two ways; a continuous variable indicating the average distance to all tourist attractions (Model 1*) and a categorical variable accounting for different classifications of the average distance to all tourist attractions (Model 2*). These classifications will be 0 – 1.5 km; 1.5 - 2.25 km; 2.25 – 3 km; more than 3 km. The aforementioned distance categories are generated using the Euclidean distance of each listing to tourist attractions calculated with the assistance of ArcGIS.

3.3 Data

As mentioned before, proximity to tourist attractions is expected to be associated with Airbnb listings' nightly rates. In order to test for this effect, similar to the work of Wang & Rasouli (2022), the major tourist attractions in Athens are being selected from the website of Tripadvisor. Tripadvisor is a worldwide known travel guidance platform that assists tourists to discover interesting places to visit during their trip (Tripadvisor.com, 2022). The ten most visited areas include sights such as the Acropolis, Parthenon, Acropolis Museum, Odeon of Herodes Atticus, Plate, Anafiotika, Panathenaic Stadium (Kallimarmaro), Lycabettus Hill, National Archaeological Museum, Benaki Museum, Museum of Cycladic Art, Byzantine and Christian Museum, Athens War Museum, National Garden, Hellenic Parliament, Filopappou Hill, Temple of Hephaestus, Ancient Agora of Athens, and Museum of Illusions. These tourist attractions are classified into 10 areas and are distributed in the city of Athens as demonstrated in Figure 3.

The dataset of Airbnb listings in Athens was sourced by an open data software from Inside Airbnb similarly to the works of Wang & Nicolau (2017). Inside Airbnb is an independent, non-commercial website that provides information on listings' attributes (opendatasoft.com, 2022). This dataset was obtained in February 2022 and contains cross-sectional observations of Airbnb listings in Athens from 2017. The initial dataset includes 5127 listings and 89 variables regarding host, property, amenity, and services attributes as well as reviews and information for the policies of the properties.

Table 1 reports the descriptive statistics of the dataset after removing from it atypical and missing values of listings in terms of nightly rates, host listings, No. reviews, hosts' listings count, No. bedrooms and No. bathrooms, as noted analytically in Appendix C. The final number of observations of the sample used in this thesis is 3.870.

Based on the dataset used in this work, the mean nightly rate of Airbnb listings in Athens is €50.91. Almost 9% of the listings are located within a 0.25 km distance from the nearest tourist attraction while almost 27% of the listings are situated from 0.25 km to 0.5 km and 25% of the listings from 0.5 km to 0.75 km from the nearest tourist attraction site. Moreover, more than 80% of Athens' Airbnbs are located within a 0.5 distance from a metro station. Only 27% of the hosts have acquired the superhost status while the mean number of properties listed by a single host is 9. 85% of the listed properties are entire houses or apartments, 14% are private rooms and only 1% are shared rooms. Approximately 60% of the listings offer 1 bedroom while more than 80% provide 1 bathroom. Regarding the provision of amenities, 97% of the properties offer real beds, only 18% entail breakfast and 12% provide free parking space, whilst no more than 0.52% provide a pool. The listings' mean reviews per month are 2 while 46% of the listings are located in the first municipal district, 17% are in the second and 13% belong to the third municipal district of Athens, as defined in Table 2.

Table 1: Descriptive statistics (No. observations = 3870)

Variable	Mean	Std. Dev.	Min	Max
Nightly rates	50.872	43.677	9	700
Natural logarithm of nightly rates	3.727	.591	2.197	6.551
Distance to nearest tourist attraction (km)	.839	.653	.005	4.35
Distance to the nearest tourist attraction				
0 - 0.25 km	.089			
0.25 - 0.5 km	.268			
0.5 - 0.75 km	.247			
0.75 - 1 km	.121			
1 - 1.5 km	.139			
1.5 - 2 km	.067			
More than 2 km	.069			
Average distance to tourist attractions (km)	1.952	.806	.983	5.707
Average distance to tourist attractions				
0 - 1.5 km	.356			
1.5 - 2.25 km	.379			
2.25 - 3 km	.152			
More than 3 km	.113			
Distance to the nearest metro station (km)	.482	.291	.014	1.958
Superhost	.275			
Hosts' Listing Count	8.972	29.619	1	769
Cancellation Policy				
Flexible	.248			
Moderate	.354			
Strict	.398			
Room Type				
Entire home/apt	.853			
Private room	.140			
Shared room	.007			
Guests Capacity	3.718	2.003	1	16
Number of Bedrooms	1.352	.82	0	10
Number of Bathrooms	1.171	.453	0	8
Pool	.005			
Real bed	.970			
Breakfast	.179			
Parking	.120			
Internet	.970			
Reviews per Month	2.018	1.848	.020	10.850
Municipal Districts				
1	.460			
2	.171			
3	.127			
4	.025			
5	.030			
6	.093			
7	.094			

Notes: *Listings without bathrooms consist of private rooms*
Listings without bedrooms provide at least one bed (possibly in the living room).

4. Empirical Results & Discussion

4.1 Baseline Models

The results of the hedonic regression analysis can be observed in Table 3. Primarily, it is important to observe the extent to which the model can explain variation in the dependent variable. The R-squared of Model 1 indicates that the independent variables explain almost 58% of the variance of Airbnb listings' nightly rates. Cited works that employed hedonic regression models find a similar magnitude of R-squared (Gibss et al., 2017, Low & Luth, 2021), implying thus that our analysis is in line with the established literature and model 1 thus provides sufficient explanatory power of nightly rates determination. Given that the dependent variable of this thesis is the natural logarithm of nightly rates, in order to derive the effect of a unitary change in the independent variables on nightly rates (as a percentage) one has to take the exponential of their coefficient, minus 1, times 100%. Therefore, if X increases by one unit, Y will, on average, increase by $(\exp(\beta_X)-1)*100$ %, ceteris paribus.

Most of this thesis' findings are in line with a priori expectations. Focusing on the distance to the nearest tourist attraction, the key-independent variable of this thesis, a greater distance to the nearest tourist attraction is, on average, associated with lower nightly rates, ceteris paribus and is significant at 1% as demonstrated in Table 3. More specifically, Model 1 indicates that, on average, a 1 km increase in distance to the nearest tourist attraction is related to 16.4% lower nightly rates, ceteris paribus. This effect is significant at 1%. Cited works observe that in three major Chinese cities a 1-kilometre rise in distance to tourist attractions is associated with a 3.1% decrease in nightly rates (Chang & Li, 2021) whilst in Amsterdam, a 1% increase in km distance to tourist spots is related to 0.16% decrease in nightly rates (Wang & Rasouli, 2022).

In addition, given that the relationship between distance to the nearest tourist attraction and nightly rates is not linear per se (Figure 4a), we alter the measurement of the key independent variable from continuous to categorical in Model 2 as noted previously. As observed, Model 2 has an R-squared of 59% indicating that the explanatory power of the model improves when distance is segregated into classifications. More specifically, listings that are located within a 0.25 – 0.5 km and a 0.5 – 0.75 km distance to the nearest tourist attraction are, on average, associated with a 15.8% and 22.3% decline in nightly rates respectively, compared to the reference category – listings that are situated within a 0.25 km to the nearest tourist attraction. Similarly, listings that are located within a 0.75 – 1 km and the ones situated within a 1 – 1.5 km distance to the nearest tourist spot are, on average, related to 29% and 33% lower nightly rates, respectively, compared to the reference category, ceteris paribus. Lastly, listings situated within a 1.5 – 2 km or more than 2 km distance to the nearest tourist site are linked with a 34% and 35.6%

decrease in nightly rates respectively, compared to the reference category, ceteris paribus. These findings are in line with the study of Perez-Sanchez et al. (2018) who by using a dummy variable, find that, on average, listings within identified tourist attractive areas are associated with 16% greater nightly rates compared to listings outside of these areas, in four Spanish cities.

Therefore, this thesis' results regarding listings' distance to the nearest tourist attraction are in line with cited studies in terms of exhibiting a statistically significant negative relationship between listings' distance to attractive sites and their nightly rates, whilst the magnitude of these effects are to a certain degree comparable with established findings. Evidently, proximity to tourist spots constitutes a crucial factor in Airbnb rates determination. As Low and Luth (2021) and Chang & Li (2021) note, a plausible explanation for this is that commonly leisure rather than business travelers choose to book an Airbnb and thus they are willing to pay a premium in order to stay in closer proximity to tourist attraction sites. Moreover, staying in listings that are closer to tourist attractions (within walking distance) offers the advantage of avoiding inconvenient means of transport to reach these spots (Low & Luth, 2021). Additionally, Wang & Rasouli (2022) note that visitors prefer to walk rather than use public transport when they are on vacation so that they can experience the streetscape as much as possible. Our work suggests that the effect of proximity to tourist attractions exhibits an impact of greater magnitude compared to the effect of proximity to metro stations on nightly rates. This implies that tourists are willing to pay a relatively higher price premium to be accommodated in proximity to attractive sites rather than staying close to a metro station at a listing that is further away from the tourist attraction sites.

Table 3. Hedonic regressions results – Key independent variable: Distance to the nearest tourist attraction		
VARIABLES	Model 1 Ln(nightly rate)	Model 2 Ln(nightly rate)
Distance to nearest tourist attraction (km)	-0.179***	
	(0.0167)	
Distance to nearest tourist attraction = 0.25 - 0.5 km		-0.172***
		(0.0255)
Distance to nearest tourist attraction = 0.5 - 0.75 km		-0.252***
		(0.0261)
Distance to nearest tourist attraction = 0.75 - 1 km		-0.342***
		(0.0316)
Distance to nearest tourist attraction = 1 - 1.5 km		-0.397***
		(0.0300)
Distance to nearest tourist attraction = 1.5 - 2 km		-0.416***
		(0.0384)
Distance to nearest tourist attraction = More than 2 km		-0.440***
		(0.0445)
Distance to nearest metro station (km)	-0.166***	-0.165***
	(0.0234)	(0.0227)
Superhost	0.186***	0.180***
	(0.0147)	(0.0145)
Hosts' Listing Count	0.00175***	0.00173***
	(0.000172)	(0.000177)
Cancellation Policy = Moderate	0.0144	0.0154
	(0.0159)	(0.0157)
Cancellation Policy = Strict	0.0130	0.0138
	(0.0172)	(0.0169)
Room Type = Private room	-0.511***	-0.506***
	(0.0208)	(0.0206)
Room Type = Shared room	-1.465***	-1.474***
	(0.0894)	(0.0890)
Guests Capacity	0.0503***	0.0517***
	(0.00763)	(0.00762)
Number of Bedrooms	0.0884***	0.0884***
	(0.0160)	(0.0157)
Number of Bathrooms	0.307***	0.299***
	(0.0351)	(0.0347)
Pool	0.663***	0.677***
	(0.0992)	(0.104)
Real bed	0.158***	0.152***
	(0.0307)	(0.0300)
Breakfast	0.0101	0.0147
	(0.0168)	(0.0165)
Parking	0.0198	0.0203
	(0.0211)	(0.0208)
Internet	0.109***	0.108***
	(0.0409)	(0.0401)
Reviews per Month	-0.0445***	-0.0443***
	(0.00362)	(0.00359)
Municipal Districts	Yes	Yes
Constant	3.160***	3.274***
	(0.0614)	(0.0643)
Observations	3,870	3,870
R-squared	0.578	0.590

Notes: The reference category for Distance to the nearest tourist attraction is 0 - 0.25 km; for Cancellation Policy: "Flexible"; for Room type: "Entire home/apartment"'.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Regarding the coefficients of Model 2 control variables and focusing on other location specifications, a 1-km increase in distance to the nearest metro station is associated with 15.2% lower nightly rates, on average ceteris paribus, as Model 2 indicates. Moreover, it must be noted that although the coefficients of the categorical variable "Municipal Districts" are not indicated in Table 3, some of them exhibit an effect that is significant at 1%. Therefore, the inclusion of this categorical variable is necessary to account for the influence of spatial differences across municipal districts on Airbnb listings' nightly rates.

Regarding the impact of host-related characteristics, hosts that have obtained the superhost status set, on average, 19.7% higher nightly rates compared to the ones that have not obtained it. Moreover, adding an additional listing to a host's owned Airbnbs is related, on average, with a 0.20% increase in listings' nightly rates. These results are in line with the findings of Wang & Nicolau (2017), Gibbs et al. (2017), and Chang & Li (2021). Further, although Wang & Nicolau (2017) and Chang & Li (2021) find that a flexible cancellation policy leads to lower nightly rates, our results indicate that there are no significant differences in nightly rates as a result of cancellation policies.

Considering the property features, private rooms and shared rooms are on average offered for 40% and 77% lower nightly rates compared to entire houses/apartments, respectively. In addition, a unitary increase in the number of guests that can be accommodated is related to a 5.3% rise in nightly rates whilst a unitary increase in the number of bedrooms and bathrooms leads to 9.2% and 34.9% higher nightly rates respectively. These findings are in accordance with the works of Wang & Nicolau (2017), Low & Luth (2021), and Gibbs et al. (2017).

As for the internal amenities, as demonstrated in Table 3, listings that provide a pool are related with 96.8% higher nightly rates compared to listings that do not offer a pool. The provision of real beds is linked with 16.4% higher rates compared to listings that provide other bed types such as airbeds or sofa beds. Similarly, listings that offer free wireless internet are, on average, linked with 11.4% greater nightly rates, compared to the ones that do not offer this amenity. The effects of these services on nightly rates are in line with the findings of Wang & Nicolau (2017), Low & Luth (2021), and Gibbs et al. (2017). However, despite the results of the cited works, the hedonic model of this thesis indicates that the provision of breakfast and free parking does not have a statistically significant impact on nightly rates.

Additionally, a unitary increase in monthly reviews leads to a 4.3% decline in nightly rates, as also found by Wang & Nicolau (2017). Overall, all of the coefficients of the aforementioned control variables included in Model 1 share the same direction and significance level, whilst their magnitude slightly differs.

4.2 Sensitivity Analysis

We acknowledge that a significant number of tourists might not be interested in booking a listing in the closest proximity to a specific tourist attraction but may prefer to be near to as many attractions as possible. Therefore, we alter the definition of the key independent variable from the distance to the nearest tourist attraction to the average distance to all tourist sites. The results of the hedonic regression analysis with the altered definition of the key independent variable are demonstrated in Table 4. As in section 4.1, proximity to tourist attractions is measured in two ways, as a continuous variable and as a categorical variable.

First, Model 1* considers the average distance to tourist spots as a continuous variable. This model explains 59% of the variation of the dependent variable (nightly rates). The coefficient of the key independent variable indicates that a 1-km increase in average distance to all tourist attractions is associated with 19.7% lower nightly rates, on average, ceteris paribus. This effect is significant at 1%.

As in section 4.1, a linear relationship between average distance to tourist sites and nightly rates is assumed in Model 1*. However, this relationship might deviate from linearity as demonstrated by Figure 4b and hence the key independent variable of this work is altered from a continuous to a categorical variable in Model 2*. This model's R-squared is 60% which is higher than the one of Model 1* by 1%. All the categories of the key independent variable are, on average, negatively correlated to nightly rates, compared to the reference category - listings located within 1.5km distance to tourist attraction sites - and significant at 1%. More specifically, listings located at 1,5km to 2,25km from tourist spots are associated with 23.7% lower nightly rates compared to the listings situated within a 1.5km distance to tourist attractions. Likewise, listings located from 2.25km – 3km to tourist spots are, on average, associated with a 28% decrease in nightly rates whilst the ones situated more than 3 km are, on average, linked with a 32.6% decline in rates compared to the reference category, ceteris paribus.

Comparing the results of the baseline models (distance to the nearest tourist attraction) and the results of the models that measure the key independent variable as the average distance to all tourist sites, a few things must be noted. First, both the effects of the distance to the nearest tourist attractions and the average distance to all tourist spots are significant at 1% whilst their magnitudes are similar to each other. Moreover, Model 1* and Model 2* demonstrate a greater R-squared by 1% compared to Model 1 and Model 2, respectively. However, we believe that this difference in the magnitude of R-squared is not adequate to indicate that tourists have a preference for being accommodated nearby all tourist attractions rather than only one. Nevertheless, the significant influence of proximity to tourist attractions on nightly rates is robust and resilient upon different operationalizations of the key independent variable (distance to the nearest tourist site or distance to all tourist attractions) and different measurement approaches (as a continuous or a categorical variable). Evidently, the findings of this thesis suggest that proximity to tourist attractions is a key determinant of Airbnb listings' nightly rates in both definitions used. Additionally, it is worth mentioning that metro stations are commonly located nearby tourist spots, as demonstrated in Figure 2. For this reason, the models of this thesis in conjunction with the effect of proximity to tourist attractions, also consider the impact of proximity to the nearest metro station on nightly rates. In this way, our findings support that the influence of proximity to tourist attractions on nightly rates, which could imply greater demand for listings in these areas, is robust and isolated from the effect of proximity to public transport.

Lastly, regarding the effects of the remaining control independent variables of Model 1* and Model 2* on nightly rates, their coefficients sustain identical statistical significance levels and direction with the two baseline models, whilst their magnitudes slightly vary. Specifically, in Model 2, a unitary increase in the number of guests that can be accommodated is associated with a 5.3% increase in nightly rates whilst in Model 2*, the same effect is related to a 4.9% rise in nightly rates. This effect in all of the models is significant at 1% and has a positive direction, indicating that as a listing's guests' capacity increases, the nightly rates increase, on average, ceteris paribus.

Table 4. Hedonic regressions results – Key independent variable: Average distance to tourist attractions

VARIABLES	Model 1 Ln(nightly rate)	Model 2 Ln(nightly rate)
Average distance to tourist attractions (km)	-0.220***	
	(0.0154)	
Average distance to tourist attractions = 1.5 - 2.25 km		-0.270***
		(0.0160)
Average distance to tourist attractions = 2.25 - 3 km		-0.328***
		(0.0263)
Average distance to tourist attractions = More than 3 km		-0.394***
		(0.0337)
Distance to nearest metro station (km)	-0.152***	-0.119***
	(0.0232)	(0.0227)
Superhost	0.185***	0.175***
	(0.0145)	(0.0142)
Hosts' Listing Count	0.00166***	0.00162***
	(0.000169)	(0.000179)
Cancellation Policy = Moderate	0.0174	0.0165
	(0.0156)	(0.0154)
Cancellation Policy = Strict	0.0115	0.0167
	(0.0169)	(0.0168)
Room Type = Private room	-0.506***	-0.490***
	(0.0206)	(0.0206)
Room Type = Shared room	-1.462***	-1.464***
	(0.0888)	(0.0864)
Guests Capacity	0.0490***	0.0481***
	(0.00760)	(0.00764)
Number of Bedrooms	0.0920***	0.101***
	(0.0159)	(0.0158)
Number of Bathrooms	0.306***	0.301***
	(0.0350)	(0.0347)
Pool	0.660***	0.685***
	(0.0962)	(0.102)
Real bed	0.149***	0.154***
	(0.0308)	(0.0309)
Breakfast	0.0101	0.0138
	(0.0166)	(0.0164)
Parking	0.0240	0.00977
	(0.0210)	(0.0207)
Internet	0.108***	0.109***
	(0.0405)	(0.0380)
Reviews per Month	-0.0475***	-0.0465***
	(0.00362)	(0.00361)
Municipal Districts	Yes	Yes
Constant	3.408***	3.170***
	(0.0659)	(0.0588)
Observations	3,870	3,870
R-squared	0.588	0.599

Notes: The reference category for Average distance to tourist attractions is 0 - 1.5 km; for Cancellation Policy: "Flexible"; for Room type: "Entire home/apartment"'.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

Overall, it is important to note that the models employed in this thesis exhibit high explanatory power of variation in nightly rates in Athens, with an R^2 of at least 58%, indicating that the independent variables used in this work are good predictors of nightly rates. This thesis adds to established literature by examining the impact of proximity to tourist attractions, measured under two different definitions - distance to the nearest spot and average distance to all sites, whilst accounting for other influential factors towards nightly rates in Athens. The impact of distance to tourist attractions on nightly rates is significant at 1%, has a negative direction and grows in magnitude as the distance to tourist spots rises across the municipality of Athens. This can be justified due to the fact that usually, tourists rather than business travelers decide to stay in an Airbnb listing and that generally, tourists prefer to walk rather than use public transport when visiting a place for leisure. Evidently, visitors are willing to pay a premium to stay in the vicinity of attractive sites.

This thesis sheds light on the determinants of Airbnb nightly rates and underlines the importance of proximity to tourist attraction sites. These insights may be valuable for hosts in setting nightly rates and for understanding which listing features matter the most for their consumers. Moreover, by defining the determinants of Airbnb rates, investors can make informed decisions regarding the allocation of their resources. More specifically, after becoming aware of the impact of locational attributes such as the proximity to tourist attractions as well as other influential attributes on nightly rates, investors can make a more accurate cost-benefit analysis based on the magnitude of their investment and their expected returns. Furthermore, the majority of Airbnb listings are located nearby tourist spots as demonstrated in Figure 1. These remarks can act as signals to the Hellenic government for understanding the importance of proximity to tourist sites in the accommodation rental market sector. In this way, it might be meaningful for the government to develop additional tourist attractions such as parks or to relocate attractive sites such as museums from the areas in which they are clustered to areas that lack such sites, and thus tourists' attention. For instance, the modern Museum of Illusions, which is located right next to the Ancient Agora of Athens (Figure 3) and was established in 2018, could be a feasible option to relocate given that its exhibitions can be easily transferred to a new location. Although such a governmental initiative may require a long-time horizon and high cost, the Greek economy may benefit from increased business activity in deprived areas (Alyakoob & Rahman, 2018). Precisely, more neighbourhoods may attract tourists, experience enhanced business activity, and become revitalized. As Alyakoob & Rahman (2018) note, increasing tourist flow in a neighbourhood is aligned with rising tourist expenditures not only for short-term accommodation but also for local businesses. Evidently, increased revenues for the local businesses and the government (through taxes) can lead to an expanded multiplier effect, contributing to the state of the economy.

Nevertheless, this study is subject to several limitations. Firstly, the dataset used in this analysis consists of cross-sectional observations and thus only considers one price at a point in time. In this way, it is not feasible to capture differences in the impact of the examined attributes on nightly rates across different seasons. For instance, listings that offer a pool are, on average, found to have 97% higher nightly rates compared to listings that do not offer one. However, this effect might not be significant in the winter season. Future studies could consider gathering panel data to examine seasonal issues such as differences in tourist demand, nightly rates, and availability of listings throughout the year. Secondly, this study, by employing hedonic regression models, does not consider price differentials across different market segments. Conducting research that investigates the effect of proximity to tourist attractions on nightly rates for low-end and high-end market listings (quantile regression) can be more meaningful for hosts and investors.

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Appendix A – Figures & Tables

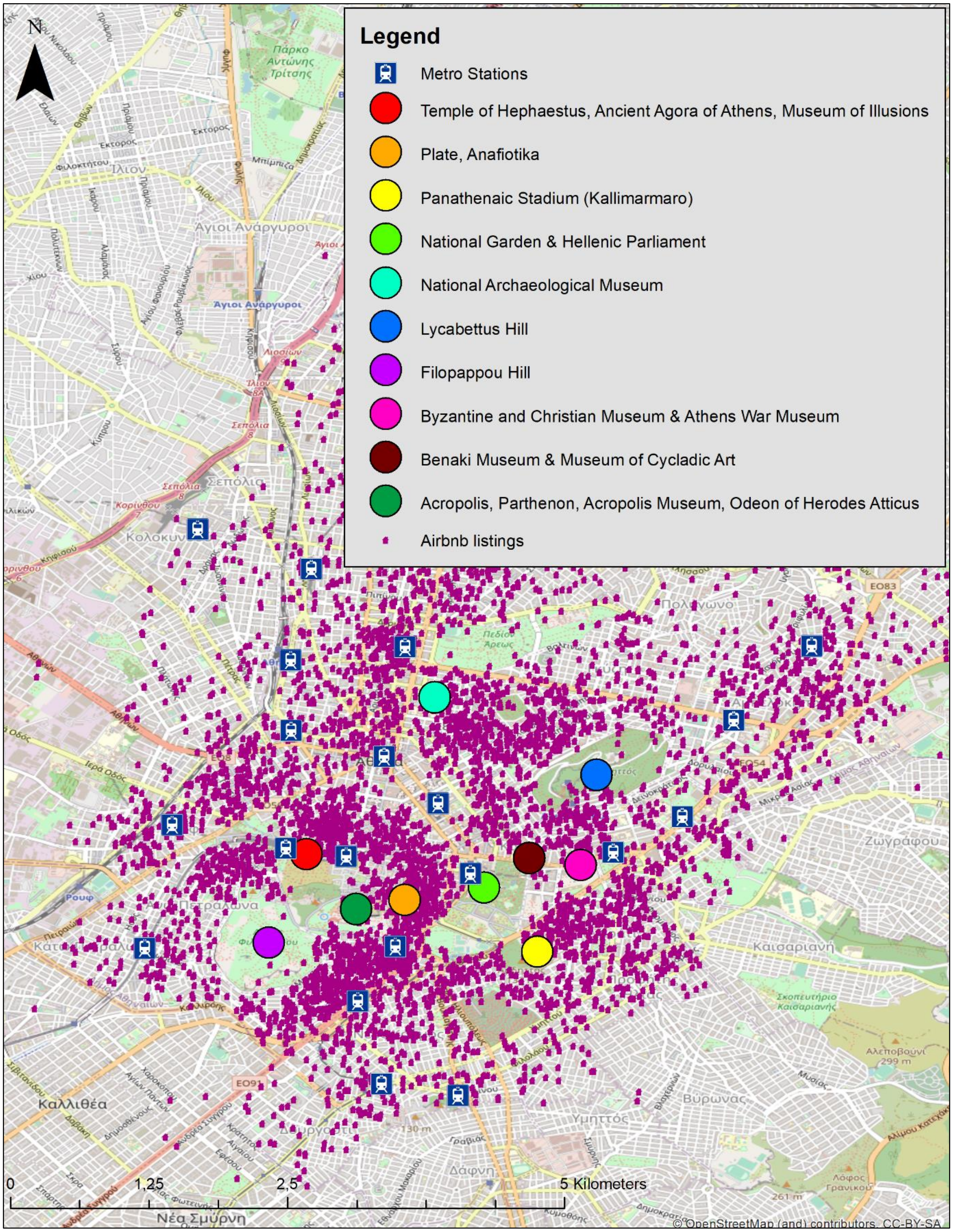
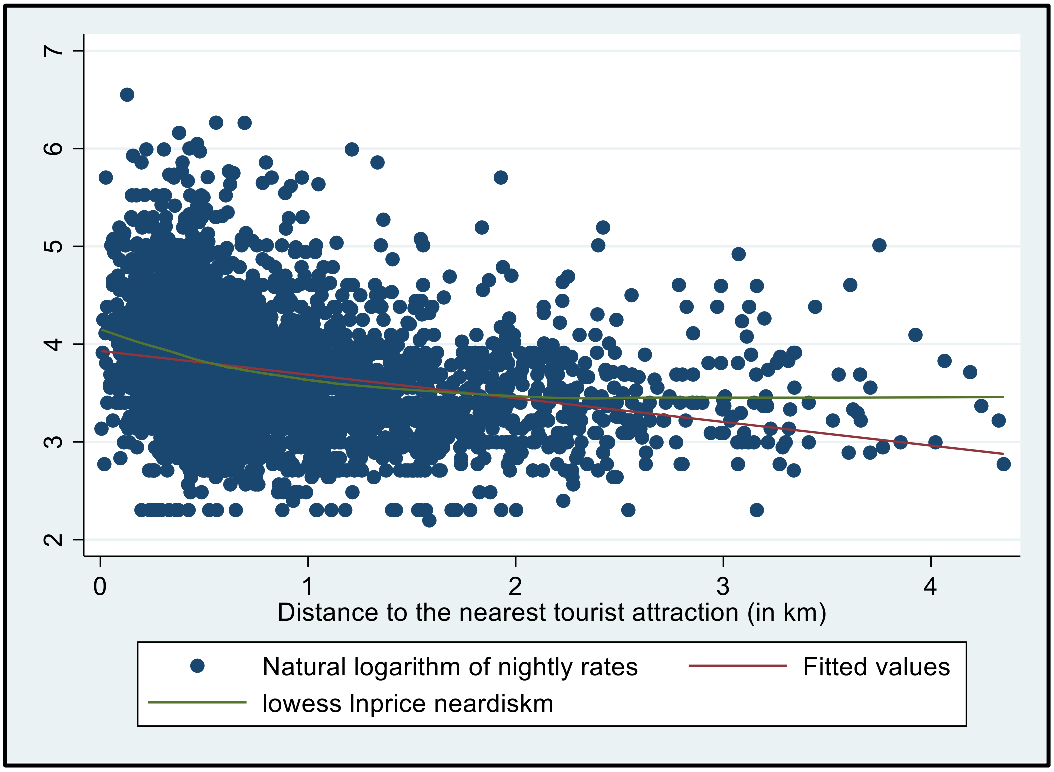


Figure 3. Descriptive analysis and spatial distribution of selected tourist attractions in Athens, Greece.
Data regarding the Airbnb listings were provided by Inside Airbnb, Tourist Attractions by Tripadvisor, whilst Metro Stations by the Hellenic Government.

Table 2: Definition & Description of variables

Variable name	Definition	Description
Listings Nightly Rates	The natural logarithm of listings' nightly rates	Continuous variable
Host-related characteristics		
Superhost	Whether the host has acquired the superhost status	Dummy variable =1 if the host is superhost; =0 if not
Host Listing Count	The number of listings that a host owns	Continuous variable
Cancellation Policy	Whether the listings' cancellation policy is flexible, moderate, or strict	Categorical variable =0 if the property's cancellation policy is flexible =1 if the property's cancellation policy is moderate =2 if the property's cancellation policy is strict
Property Features		
Guests Capacity	The number of guests that can be accommodated	Continuous variable
Bedrooms	The number of bedrooms available in each listing	Continuous variable
Bathrooms	The number of bathrooms available in each listing	Continuous variable
Services		
Real bed	Whether the listing provides a real bed	Dummy variable =1 if the property has a real bed; =0 if not
Wireless internet	Whether the listing provides wireless internet	Dummy variable =1 if the property has wireless internet; =0 if not
Breakfast	Whether the listing provides breakfast	Dummy variable =1 if the nightly rate includes breakfast; =0 if not
Free parking	Whether the listing provides free parking	Dummy variable =1 if the property has free parking; =0 if not
Pool	Whether the listing has a pool	Dummy variable =1 if the property has a pool, =0 if not
Number of Reviews		
Average Reviews per Month	The listings' average reviews per month	Continuous variable
Locational characteristic		
Average distance to tourist attraction	The average distance from a listing to all tourist attractions in km	Continuous variable
Average distance to tourist attraction (categorical variable)	0 – 1.5 km 1.5 – 2.25 km 2.25 – 3 km More than 3 km	=1 if the property's average distance to sites is no more than 1.5km =2 if the property's average distance to sites is from 1.5 to 2.25 km =3 if the property's average distance to sites is from 2.25 to 3 km =4 if the property's average distance to all sites is over 3 km
Nearest distance to tourist attraction	The distance from a listing to the nearest tourist attraction in km	Continuous variable
Distance to the nearest tourist attraction (categorical variable)	0 - 0.25 km 0.25 - 0.5 km 0.5 - 0.75 km 0.75 – 1 km 1 - 1.5 km 1.5 – 2 km More than 2 km	=1 if the property is located within 0.25 km from the nearest site =2 if the property is located from 0.25 to 0.5 km to the nearest site =3 if the property is located from 0.5 to 0.75 km to the nearest site =4 if the property is located from 0.75 to 1 km to the nearest site =5 if the property is located from 1 to 1.5 km to the nearest site =6 if the property is located from 1.5 to 2 km to the nearest site =7 if the property is located over 2 km away to the nearest site
Distance to the nearest metro station	The distance from a listing to the nearest metro station in km	Continuous variable
Municipal Districts (Categorical variable)	1: Stadio, Omonoia, Plaka 2: Southeast neighbourhoods 3: Southwest neighbourhoods 4: West neighbourhoods 5: Northwest neighbourhoods 6: Middle-north neighbourhoods 7: Northeast neighbourhoods	=1 if the property is located in the 1^{st} municipal district =2 if the property is located in the 2^{nd} municipal district =3 if the property is located in the 3^{rd} municipal district =4 if the property is located in the 4^{th} municipal district =5 if the property is located in the 5^{th} municipal district =6 if the property is located in the 6^{th} municipal district =7 if the property is located in the 7^{th} municipal district

Distance to the nearest tourist attraction (km – continuous variable)



Distance to the nearest tourist attraction (categorical variable)

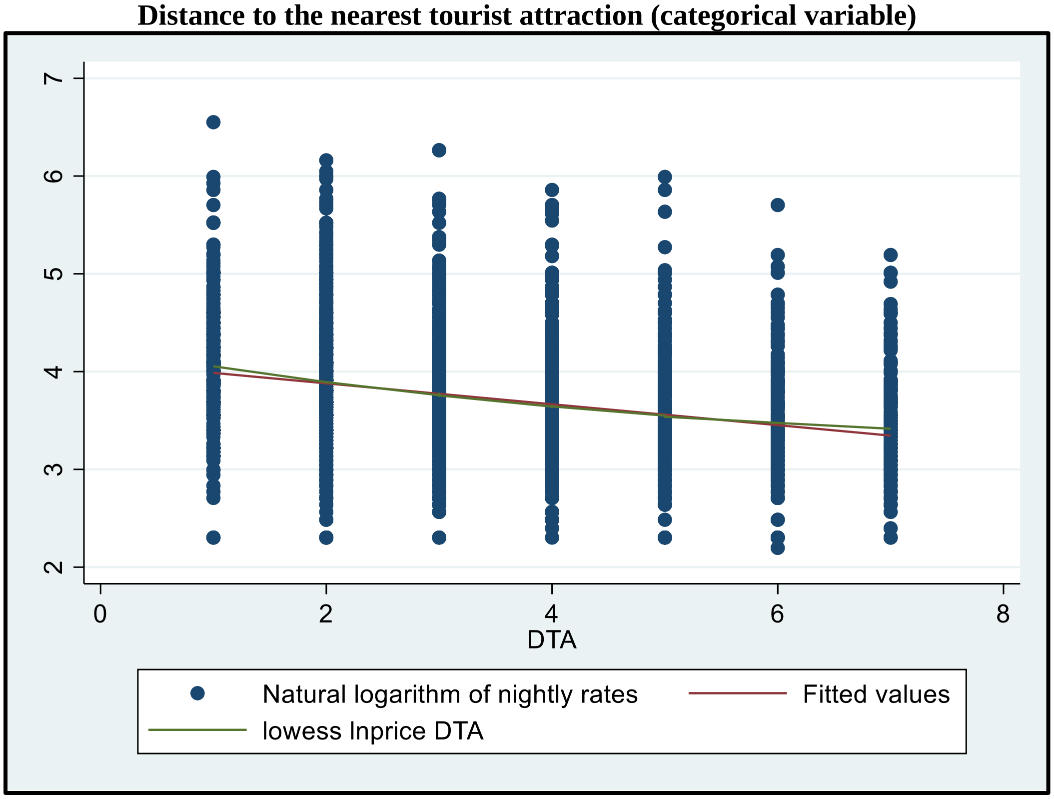
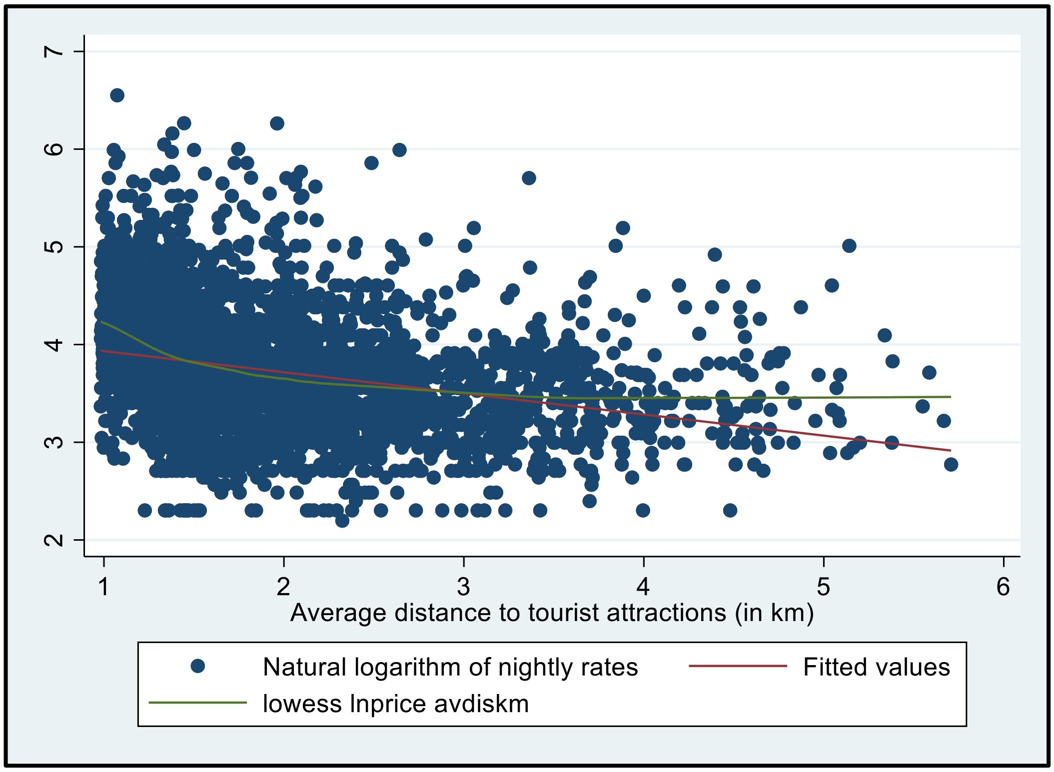


Figure 4a. Relationship between nightly rates and distance to the nearest tourist attraction

Notes: lnprice refers to the natural logarithm of nightly rates whilst DTA refers to the distance to the nearest tourist attraction.

Average distance to tourist attractions (km – continuous variable)



Average distance to tourist attractions (categorical variable)

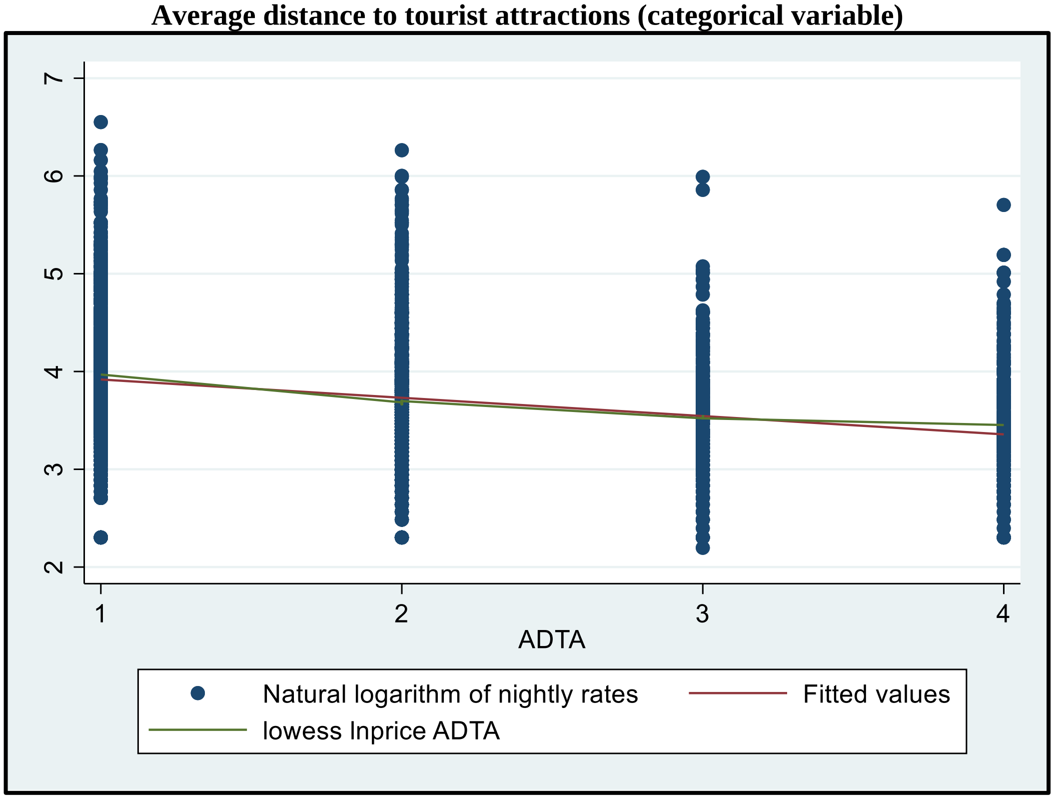


Figure 4b. Relationship between nightly rates and average distance to tourist attractions

Notes: lnprice refers to the natural logarithm of nightly rates whilst ADTA refers to the average distance to all tourist attractions.

Appendix B – OLS assumptions.

Assumption 1 - Linear error terms – E(εt) = 0

According to Brooks and Tsolacos the first of the OLS assumptions that concern the linearity of the residuals will never be violated when a constant term (β0) is incorporated into the regression model. Therefore, since every model of this thesis includes an intercept term, it is assumed that this assumption is fulfilled.

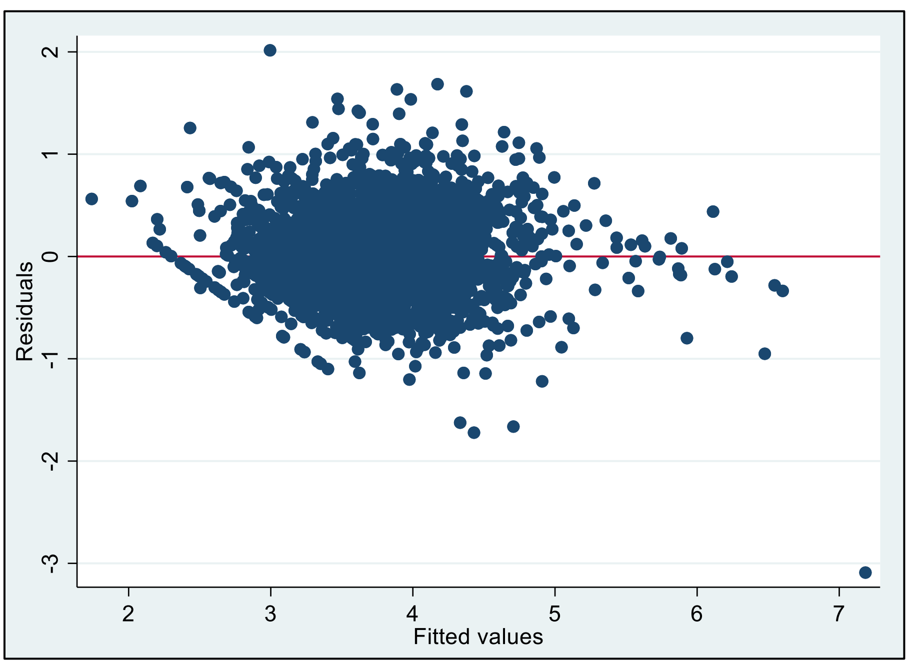
Assumption 2 - Constant error terms –Var(εt) = $\sigma^2 < \infty$

To check for the second OLS assumption regarding the presence of homoscedastic error terms, the Bruesch-Pagan/Cook-Weisberg test is employed. The null hypothesis of this test is that the residuals' variance is constant. The H0 hypothesis is rejected (at a 5% significance level) in all of the models since the p-value is less than 0.05, indicating that the variance of the error terms is not constant. To mitigate the presence of heteroscedasticity, robust standard errors are being used in the regression models.

H0: Constant variance

chi2 = 179.65

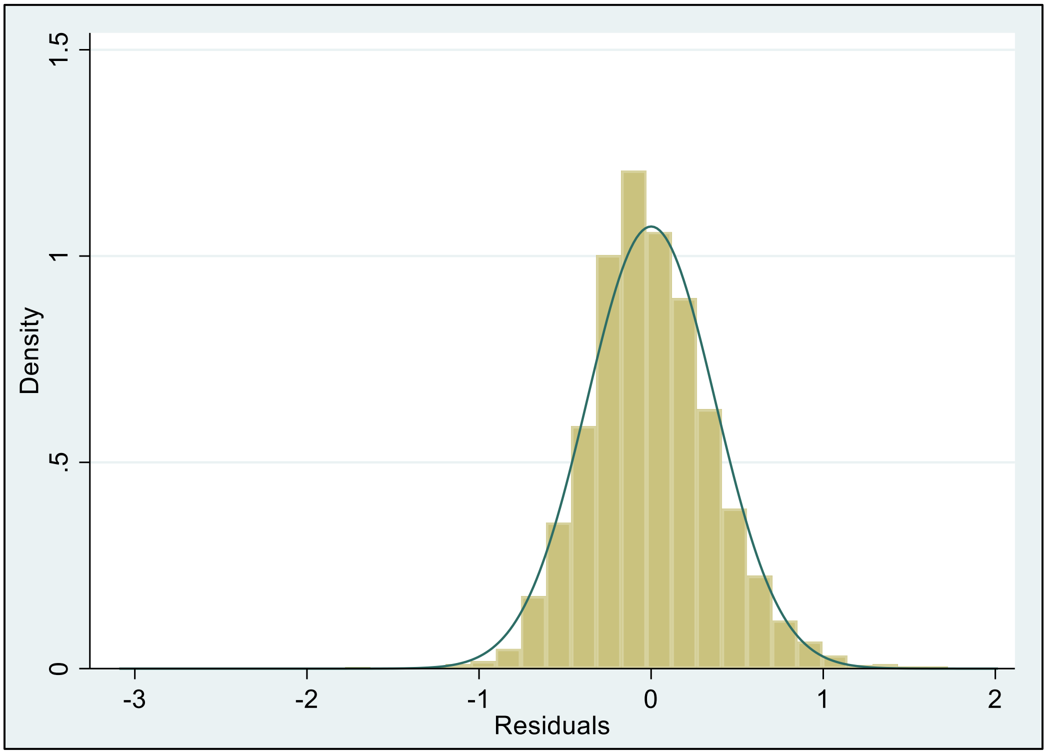
Prob > chi2 = 0.0000



Assumption 3 – Autocorrelation of the error terms –Cov(εi, εj) = 0 for i=j

The third OLS assumption requires that the residuals are uncorrelated with each other. Since the sample of this thesis consists of cross-sectional observations, it can be evident that the covariance between the residuals is zero and thus, there is no issue of autocorrelation in our sample.

Assumption 4 - Normally distributed error terms – ε ~ N(-,-)



As indicated by the figure demonstrated above, the distribution of the residuals in all of this thesis models presents a slight deviation from the normal. However, this seems to be a minor deviation and therefore it can be assumed that the residuals are normally distributed.

Multicollinearity

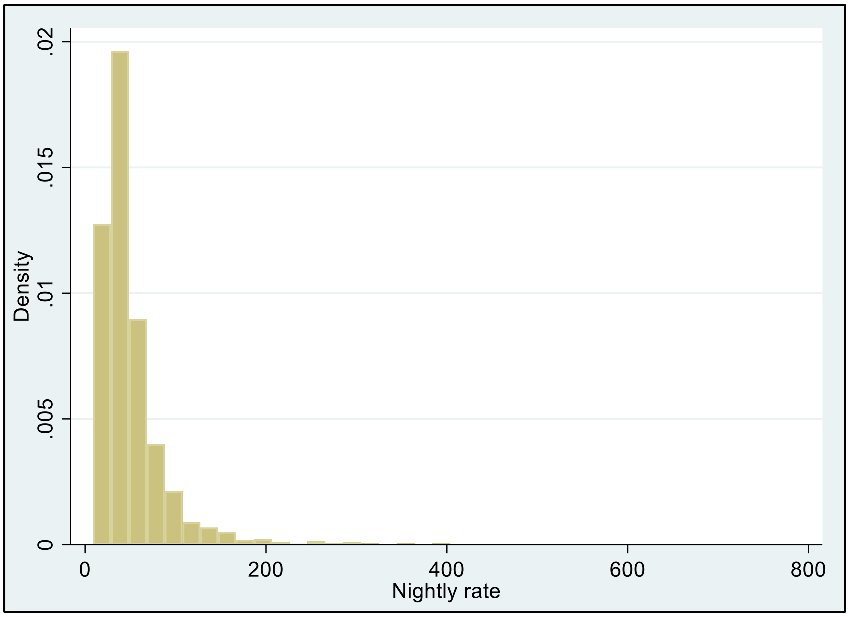
Multicollinearity is an implicit assumption that tests whether the independent variables are correlated with each other (Brooks & Tsolacos, 2010). Multicollinearity issues can be detected by the Variance Inflation Factor. Values greater than 10 indicate the existence of multicollinear factors whilst values higher than 5 signal possible multicollinearity issues. As demonstrated in the table below, all VIF values are significantly lower than 5, and thus it is evident that there are no multicollinearity issues in all of this thesis' empirical models.

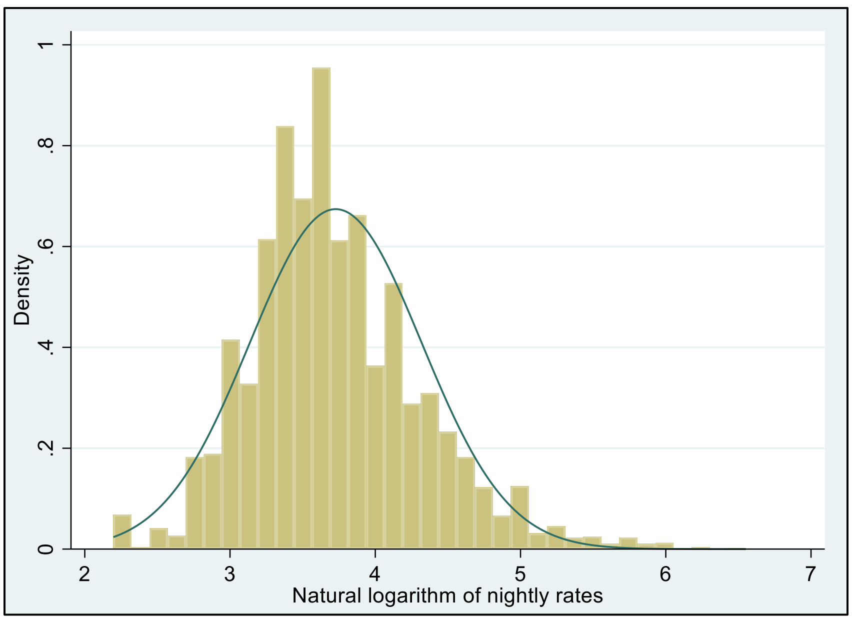
Variance inflation factor

	Model 1	Model 2	Model 1*	Model 2*
DNTA (km)	3.043			
DNTA (0.25 – 0.5 km)		2.961		
DNTA (0.5 – 0.75 km)		2.952		
DNTA (0.75 – 1 km)		2.359		
DNTA (1 – 1.5 km)		2.765		
DNTA (1.5 – 2 km)		2.341		
DNTA (More than 2 km)		3.603		
ADTA (km)			3.947	
ADTA (1.5 – 2.25 km)				1.59
ADTA (2.25 – 3 km)				2.516
ADTA (More than 3 km)				3.315
DNM	1.169	1.184	1.168	1.185
Superhost	1.182	1.193	1.182	1.186
Hosts' Listing Count	1.062	1.064	1.064	1.064
Moderate Cancellation Policy	1.657	1.66	1.657	1.657
Strict Cancellation Policy	1.738	1.738	1.738	1.739
Private room	1.166	1.171	1.167	1.174
Shared room	1.04	1.042	1.04	1.04
Guests Capacity	2.413	2.421	2.414	2.415
Number of Bedrooms	2.333	2.338	2.333	2.346
Number of Bathrooms	1.601	1.609	1.601	1.603
Pool	1.038	1.039	1.038	1.038
Real bed	1.024	1.026	1.024	1.024
Breakfast	1.024	1.026	1.023	1.025
Parking	1.094	1.094	1.091	1.086
Internet	1.035	1.037	1.035	1.036
Reviews per Month	1.199	1.2	1.207	1.204
Municipal District 2	1.288	1.358	1.251	1.249
Municipal District 3	1.241	1.335	1.465	1.551
Municipal District 4	1.399	1.476	1.454	1.468
Municipal District 5	2.246	2.35	2.46	1.907
Municipal District 6	1.476	1.587	1.822	1.922
Municipal District 7	1.892	1.938	2.302	2.177
Mean VIF	1.478	1.724	1.567	1.563

Notes: DNTA refers to "Distance to the Nearest Tourist Attraction", DNM refers to "Distance to the Nearest Metro Station", and ADTA refers to "Average Distance to Tourist Attractions".

Appendix C – Transformation of the dependent variable & Data Cleaning





Six observations that do not include a nightly rate and two that have zero host listings are excluded from the sample. Moreover, listings that are located outside of the boundaries of the municipality of Athens (26) are removed from the sample. Additionally, listings with no reviews (1214) and atypical values of the hosts' listings count (4) are also excluded from the sample. Lastly, 4 properties that do not include the number of bedrooms and 5 properties, that are missing the number of bathrooms, are omitted. The final number of observations of the sample used in this thesis is 3.870. Eventually, we derive the descriptive statistics of this thesis (Table 1) after cleaning the variables used in this work.