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The Impact of Antecedents on Airbnb Listing Prices: Evidence from Greece

Abstract. The study investigates varied effects that price antecedents have on Airbnb listings. Using data on 31705 listings from four major Greek regions (Athens, Thessaloniki, Crete, and the South Aegean), which appeared on Airbnb in December 2022 and were recorded by Inside Airbnb, the authors apply statistical tests and regression analysis to identify key pricing determinants. The results confirm the existence of evident differences in prices depending on external variables, such as the listing's region, and internal listing qualities and host attributes. The findings offer valuable insights that individual hosts, professional listing administrators, and policymakers can use to adjust pricing strategies and regulations to changes taking place in the dynamic Airbnb market in Greece.

Keywords: sharing economy, price determinants, Airbnb

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1. Introduction

There is much research interest in pricing techniques used by accommodation hosts because of their critical role in commercial peer-to-peer (P2P) accommodation platforms (APS), where the marginal cost is nearly zero (Roma et al., 2019). Despite substantial research on the pricing of commercial P2P APS, many consider this area of study to be in its infancy (Cai et al., 2019). Moreover, even though the pricing dynamics of short-term rental platforms like Airbnb have been extensively studied, regional disparities and the interplay of locational, structural, and trust-related factors remain underexplored. Latinopoulos (2018) underscores the criti-

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cal role of aesthetic and locational attributes in pricing decisions, particularly in coastal regions. Similarly, Arvanitidis et al. (2020) point out that professional hosts leverage institutional trust mechanisms such as the Superhost badge to command higher prices, contrasting with casual hosts, who rely more on interpersonal trust. This article draws on information from a dataset of Airbnb listings to identify factors influencing P2P accommodation prices in regions with diverse tourism characteristics, such as Greece. The authors employ the Shapley decomposition of R-squared to assess the relative importance of various groups of variables, such as listing characteristics (e.g., private rooms vs. entire homes/apartments), host characteristics, reviews, location, and seasonality.

The following hypotheses were put forward:

- **H1:** Listings in island regions command higher prices than urban listings because of a premium associated with leisure destinations.
- **H2:** Property attributes (e.g., number of bedrooms, amenities) and host characteristics (e.g., the Superhost status) significantly influence listing prices.

2. Literature Review on Price Antecedents for P2P Lodgings

Unlike other sharing economy services such as Uber, Airbnb hosts can establish their own prices (Benítez-Aurioles, 2018). Studies have employed hedonic regression models to investigate how different host and listing attributes affect prices, using large data sets including listings from various destinations worldwide (Kakar et al., 2018; Teubner et al., 2017). According to these studies, factors like positive review scores, offering an entire home (rather than shared accommodation), a higher number of bedrooms and bathrooms, a higher guest capacity, Superhost status, a longer time as a member, certain amenities (such as a parking lot), and a higher number of photos all result in higher prices. In contrast, factors like distance from the city centre, many listings, more flexible cancellation rules, fast booking availability, and a higher review count have been linked to lower prices.

However, studies have also found variations in pricing patterns across different destinations or reported results that depart from these general patterns (Gibbs et al., 2018). For instance, Kakar et al. (2018) discovered that cancellation policies had no significant impact on pricing, while neither Teubner et al. (2017) nor Chen and Xie (2017) discovered that the Superhost status had a substantial impact on pricing. Additionally, studies have revealed that certain attributes that would normally associate with higher prices, such as flexible cancellation policies, instant booking availability, and a greater review count, may actually be correlated with lower prices. Various explanations have been offered for this phenomenon: it has been argued that hosts use lower prices and more appealing booking policies to encourage demand (Benítez-Aurioles, 2018), or that commercially oriented hosts are more likely to use instant booking and lower prices (Gibbs et al., 2018), or that hosts with high review volumes are more likely to offer lower prices for listings with low rating scores (Teubner et al., 2017).

Dudás et al. (2020) found that certain factors related to the property, such as air conditioning, free internet access, free parking, the number of bedrooms, and the option to book either the full house or just a room, can influence the pricing of Airbnb accommodations. The variables used in Airbnb listings can be divided into several subgroups, including the type of listing (shared room, private room, entire home/apartment), size (area, number of bedrooms, bathrooms, and maximum occupancy), amenities (internet, cable TV, air conditioning, heating, pool, gym, free parking, etc.), and rental policies (instant booking, minimum stay, cancellation policy, security deposit, cleaning fee, and extra guest fee). The number of listings to differentiate between family and professional hosts (Deboosere et al., 2019), the number of images (Perez-Sanchez et al., 2018), membership or experience (Xie et al., 2019), response rate and time (Gunter & Önder, 2018), and verified identification (Abrate & Viglia, 2019) are all variables that can be grouped under the "superhost" label.

Moreover, pricing strategies are also affected by host attributes. Arvanitidis et al. (2020) distinguish between professional and casual hosts, showing that the former ones effectively leverage institutional trust mechanisms, such as Airbnb's Superhost badge, to command higher prices. According to Heo et al. (2019), hosts with verified identities and extensive positive reviews consistently outperform their peers in competitive urban markets. These findings align with the results reported by Chattopadhyay & Mitra (2020), who identified host experience and listing characteristics as critical determinants of pricing decisions.

Furthermore, Lorde et al. (2019) demonstrated that criteria such as location, reputation, convenience, host, and amenities had a substantial impact on pricing in the Caribbean. Lawani et al. (2019) investigated three categories of variables for their effects on the cost of a reservation: structural variables (such as the number of bedrooms and bathrooms), neighbourhood variables (such as the distance in feet to the nearest convention centre and train station), and quality-signalling variables (such as cleanliness, the number of reviews, and communication). They discovered that price was influenced by factors such as review quality, room attributes, and neighbourhood factors. Last but not least, Teubner et al. (2017) reported how host reputation might influence price.

The distinction between urban and leisure locations also significantly influences the pricing dynamics of Airbnb listings, reflecting a complex set of factors that shape host strategies and consumer behaviour. Prior research has underscored the importance of locational attributes, trust mechanisms, and host practices in determining short-term rental prices. Urban areas with rich leisure offerings tend to demand higher prices capitalising on tourists seeking proximity to attractions. For instance, Moreno-Izquierdo et al. (2019) demonstrated that listings in tourism-oriented urban environments derive added value from online reputations, which directly impact prices. Latinopoulos (2018) corroborates this finding in the Greek context by reporting the substantial influence of locational attributes, such as proximity to coastal attractions, on pricing. Similarly, Hong & Yoo (2020), used a Multiscale Geographically Weighted Regression (MGWR) approach to find that spatially heterogeneous pricing determinants were closely tied to unique characteristics of urban landscapes. The spatial distribution of Airbnb listings also plays a pivotal role in shaping pricing dynamics. Boutsioukis et al. (2019) mapped the uneven distribution of short-term rentals in Greece, finding significant concentrations in high-demand tourism regions such as the Cyclades and Crete. This regional clustering highlights the importance of locational characteristics in driving both pricing and supply disparities.

Table 1. Key studies on accommodation pricing determinants in Greece

Author(s)	Objective	Methods	Scope	Key findings
Latinopoulos (2018)	Assessing the impact of sea views on hotel pricing	Spatial hedonic pricing model	Coastal Halkidiki, Greece	Sea views significantly enhance pricing; aesthetic value varies by location.
Boutsioukis et al. (2019)	Mapping spatial distribution of short-term rentals across Greece	Spatial data analysis using Airbnb scraper	Nationwide	Listings are concentrated in touristic hubs like the Cyclades; regional disparities noted.
Arvanitidis et al. (2020)	Comparing professional and casual hosts' pricing strategies	Hedonic pricing model, Blinder–Oaxaca decomposition	Airbnb listings in Athens, Greece	Professionals leverage institutional trust (e.g., Superhost badge); casual hosts rely on interpersonal trust.

Source: Authors' own analysis

Such unique characteristics in tourism pricing can be found in the Mediterranean region, for example in Greece. Latinopoulos (2018) utilised a spatial hedonic model to quantify the impact of locational attributes such as sea views on hotel pricing, demonstrating the significant value of aesthetic characteristics in coastal tourism in Greece. Arvanitidis et al. (2020) explored the role of trust in Airbnb pricing, revealing a dichotomy between professional and casual hosts' reliance on institutional versus interpersonal trust mechanisms. Boutsioukis et al. (2019)

mapped the spatial distribution of Airbnb listings in Greece, highlighting a concentration in touristic regions and underscoring regional disparities in rental activity. Table 1 summarises these three studies:

Overall, price factors listed in the literature are often divided into two broad categories:

Category 1 – Internal price antecedents: Listing characteristics and host characteristics. Listing variables can be further subdivided into listing type, size, amenities, and rental policy. Host variables include the Superhost badge, number of listings, number of photos, membership or experience, response rate and time, and verified identity. Internal variables play a crucial role in determining Airbnb prices, as shown by studies such as Dudás et al. (2020), Lawani et al. (2019), and Teubner et al. (2017).

Category 2 – External price antecedents: Guest reviews, which are operationalised using the number of reviews and total rating (Lorde et al., 2019; Lawani et al., 2019), are the most important external variable. Other important factors include accessibility to sites of interest, distance to the city centre, and other local attractions such as beaches, conference centres, and transportation. The popularity of particular listings can also be influenced by social and economic characteristics of the destination, such as population age, population density, ethnic diversity, unemployment rate, per capita GDP, and housing value. Seasonal patterns of demand fluctuations over twelve months are also considered in some studies (Deboosere et al., 2019; Moreno-Izquierdo et al., 2019).

3. Data & Methodology

3.1. Study Area and Dataset

The following study focused on four regions of Greece – Athens, Thessaloniki, Crete, and the South Aegean, which were chosen for their representation of urban and leisure tourism markets. These regions exhibit different pricing dynamics, with urban centres characterised by year-round activity and islands marked by seasonal peaks. The dataset analysed in the study contained details of Airbnb listings from these four major tourist regions, as presented on the platform in December 2022. Of the total of 64698 listings recorded in these four regions, 31705 were included in the analysis after eliminating records containing critical missing values and outliers (e.g. extreme price points, incomplete host profiles). The finally selected subset of accommodations is characterised by the following descriptive statistics (Table 2):

Table 2. Descriptive statistics of the selected subset of accommodations

Average price per night	€119.86
Average number of visitors	4
Location distribution (%):	
– South Aegean	37.4
– Crete	33.0
– Athens	23.2
– Thessaloniki	6.4
Accommodation type distribution (%):	
– Whole houses/apartments	90.1
– Private rooms	8.4
– Hotel/shared rooms	1.6
Review data:	
– Average review score	4.79 / 5.00
– Average number of reviews per listing	35
Host profiles:	
– Superhost badge holders	33.0%
– Average years on Airbnb	Over 5
– Average number of listings	25 (including property management companies)

Source: Authors' own analysis

The goal of the analysis was to assess the impact of nine listing variables, grouped into the following categories: accommodation variables (visitors, bedrooms, beds, bathrooms, and number of specific facilities such as internet connection, appliances, etc.), type of property, location of the listing, and license type. The data were acquired from a third-party website, insideairbnb.com, which represents an organisation with the vision of highlighting the impact of Airbnb on residential communities. The website stores publicly available details of Airbnb listings from various regions around the world.

3.2. Data Analysis

In order to identify different categories of listings with different price distributions, we employed Mann-Whitney U tests for comparing two categorical groups, and Kruskal-Wallis tests for comparing three or more categorical groups. The Mann-

Whitney U test (also known as the Wilcoxon rank-sum test) is a non-parametric statistical hypothesis test, which is used to compare two independent samples with a view to determining whether two populations have the same distribution (Mann & Whitney, 1947). The Mann-Whitney U test statistic is calculated as follows:

$$U = \frac{n_1 n_2}{2} + \frac{n_1(n_2 + 1)}{2} - R_1 \quad (1)$$

where R_1 is the average rank of the observations in group 1, and n_1 and n_2 are the sample sizes of the two groups being compared.

The nonparametric Kruskal-Wallis test can be used to determine whether there are any significant differences between two or more independent groups for a continuous or ordinal dependent variable (Kruskal & Wallis, 1952).

$$H = \frac{12}{N(N+1)} + \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \quad (2)$$

where N represents the overall sample size, k denotes the number of groups being compared, n_1 represents the sample size for group i, R_i denotes the total rank for group i, and H represents the Kruskal-Wallis test statistic.

In the second step, the listing price served as the dependent variable, and OLS regression was used to examine correlations between the independent variables to identify the strongest price determinants. Additionally, the correlation between the listing prices and continuous variables was examined using the Pearson and Spearman correlation coefficients when they were employed as independent variables.

Ordinal least squares (OLS) regression is a popular approach for modelling the relationship between a dependent variable and one or more independent variables (Gujarati et al., 2009). The goal of this method is to minimise the sum of the squared residuals between the observed and anticipated values. The equation of OLS regression is represented as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \quad (3)$$

where y is the dependent variable, x_1, x_2, …, x_k are the independent variables, β_0, β_1, β_2, …, β_k are the regression coefficients, and ε is the error term.

The linear link between two continuous variables can be measured by the Pearson correlation coefficient (Pearson, 1895). Its value falls between –1 and 1, with

−1 denoting a perfectly negative linear relationship, 0 suggesting no linear relationship, and 1 indicating a perfectly positive linear relationship. The Pearson correlation coefficient can be calculated with the following formula:

$$r_{xy} = \frac{\sum_{i-1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i-1}^{n}(x_i - \bar{x})^2 \sum_{i-1}^{n}(y_i - \bar{y})^2}} \qquad (4)$$

where r_{xy} is the correlation coefficient between x and y, n is the sample size, x_i and y_i are the i-th observations of x and y, and $\bar{x}$ are $\bar{y}$ the sample means of x and y, respectively.

The monotonic relationship between two variables is measured by the Spearman correlation coefficient (Spearman, 1904). It has a range of −1 to 1, where −1 denotes a fully negative monotonic relationship, 0 denotes a lack of monotonicity, and 1 denotes a perfectly positive monotonicity relationship. The equation representing the Spearman correlation coefficient is the following:

$$H = \frac{6\sum_{i-1}^{n}(d_i)^2}{n(n^2 - 1)} \qquad (5)$$

where ρ is the Spearman correlation coefficient, n is the sample size, and d_i is the difference between the ranks of the i-th observation of the two variables.

4. Empirical Results

The results are presented in two main sections: (1) the comparative analysis of pricing across urban and island regions, and (2) the evaluation of property attributes and host characteristics as price determinants.

Initially, the analysis focused on listing location. Therefore, listings in Athens and Thessaloniki were classified as "Urban" and those situated in Crete or the South Aegean were classified as "Island". The differences in Airbnb listing prices between urban and island regions were analysed using Mann-Whitney U and Kruskal-Wallis tests. Figure 1 shows the distribution of prices depending on the urban/island distinction and the region. Listings in island regions (Crete and the South

Aegean) were significantly more expensive than those in urban centres (Athens and Thessaloniki). The Mann-Whitney U test statistic was 48.28 (p-value < 0.05), confirming a statistically significant difference in prices between urban and island listings. On average, island listings commanded a premium of €56 per night compared to urban listings (OLS regression coefficient = 56.00, p-value < 0.05). There are also statistically significant disparities in the distribution of prices across the four major regions of Greece (the Kruskal-Wallis test: H = 2726.13, p-value < 0.05). Listings in the South Aegean charged the highest average prices (€140), followed by Crete (€110), Athens (€85), and Thessaloniki (€72). Regression analysis indicated that listings in Athens and Thessaloniki were, on average, €64 and €74 cheaper than those in the South Aegean, respectively (p-value < 0.05).

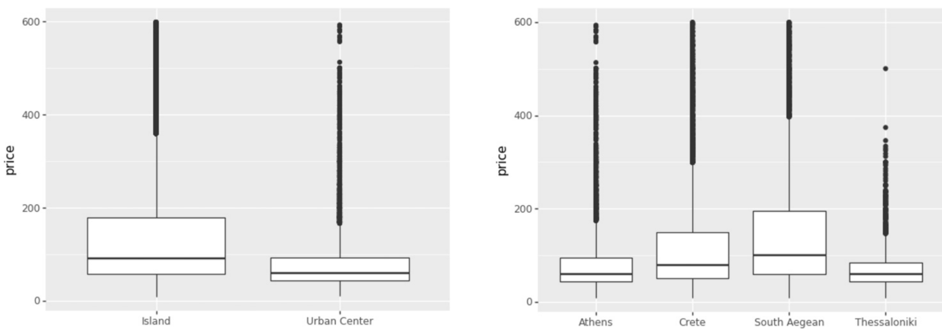

Figure 1. Price distribution of listings in urban destinations and islands in four regions of Greece
Source: Authors' own analysis

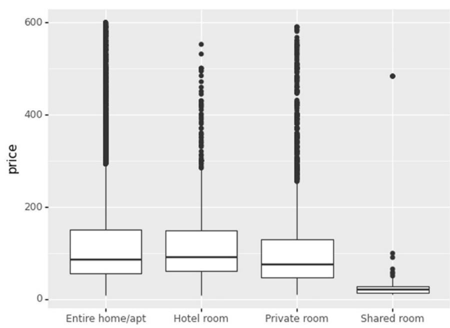

Figure 2. Price distribution of listings for different room types
Source: Authors' own analysis

Figure 2 shows price differences according to the property type, which were found to be statistically significant based on the results of the Kruskal-Wallis test (p-value < 0.05). Results of OLS regression calculated for the property types used as independent variables and the Entire Home or Apartment serving as the reference base indicate that hotel rooms were on average cheaper by €16, private rooms by €32, and shared rooms by €104, all with p-values lower than 0.05, which means that the differences were statistical significant.

Another important group of variables that determine the price of a listing are its characteristics. Their effects are analysed below.

The number of bedrooms

Values of the Spearman and Pearson correlation coefficients, 0.21 and 0.22, respectively, with a p-value < 0.05 in both cases, indicate a statistically significant, positive but rather weak correlation between the number of bedrooms and the listing price. The coefficient of determination, or R-squared, calculated for the OLS regression model was equal to 0.32, which represents the percentage of the variance in the price that the number of bedrooms explains. According to the model, a single unit increase in the number of bedrooms would increase the price of the listing by €58.25.

The number of visitors

In this case, the positive correlation was found to be stronger, with a Pearson coefficient of 0.54 and a Spearman coefficient of 0.53 with p-value < 0.05 in both cases. Results of OLS regression, indicate that this variable explains 28.9% of the variance in the price ($r^2 = 0.289$). According to the model, with a p-value < 0.05, the addition of one visitor would raise the price by €25.

The number of bathrooms

The correlation between this variable the price was also found to be positive, with a Pearson coefficient equal to 0.59 and a Spearman coefficient of 0.50, both statistically significant with p-value < 0.05. According to the regression model, the variable explains 34.3% of the variance in the price, where 1 unit increase in the number of bathrooms would increase the price by €76.

The number of amenities

The number of amenities such as the Wi-Fi connection, parking spot, utilities, etc., was found to be positively though weakly correlated with the price, with a Pearson coefficient of 0.22 and a Spearman coefficient of 0.21, both statistically significant with a p-value of 0.00. With an average number of 35 amenities per listing, every additional amenity would increase the price of the listing by €1.5. The variable was found to explain only 5% of variation in the price.

To gain a deeper understanding of this factor, two key amenities were analysed separately: the Wi-Fi connection and free parking spot.

Wi-Fi connection

The result of the Mann-Whitney U test showed that there was a statistically significant difference between the price of listings with and without Wi-Fi connection, with a p-value < 0.05. The OLS regression model indicated, that, on average, a listing with a Wi-Fi connection was €26 more expensive per night.

Free parking spot

The value of a Mann-Whitney U test indicated a statistically significant difference in the prices of listings with and without a free parking spot, with a p-value < 0.05. A listing with a free parking spot was found to be, on average, €23 more expensive per night than a listing without a parking spot.

Review scores

In this case, there was a very weak positive correlation (a Pearson coefficient of 0.10, and a Spearman coefficient at 0.22); both values were statistically significant with p-values < 0.05 respectively. According to the OLS regression model, a 0.10 increase in the overall review score would on average increase the price per night by €2.98.

Host characteristics

A statistically significant difference (p-value < 0.05) was also found to exist between review scores of listings offered by superhosts and hosts.

In summary, prices of urban listings were found to be significantly lower than those of island ones, with the highest prices charged for listings located in the South Aegean. Listing attributes, including the number of bedrooms, bathrooms, and amenities, turned out to be strong determinants of prices, with each additional bedroom and bathroom correlated with substantially higher prices. Amenities such as Wi-Fi and free parking were also found to be associated with higher prices. Host characteristics, particularly the Superhost status and the length of presence on the platform, were also found to have an effect, highlighting the importance of institutional trust and professional management. While review scores had a modest effect, they were indicative of quality and guest satisfaction.

5. Discussion

The above findings describe the multifaceted factors influencing Airbnb pricing in Greece. As can be expected, location turned out to be a key determinant of prices, contributing to statistically significant disparities between urban and island regions. Listings in the South Aegean and Crete were substantially more expensive than those in Athens and Thessaloniki. This is consistent with the findings reported by Latinopoulos (2018), who noted that locational attributes, such as scenic views and proximity to coastal attractions, were associated with higher prices. The observed premium for island listings shows the importance of leisure-oriented demand and verifies the hypothesis that location plays a critical role in determining short-term rental prices.

Prices of listings are also strongly correlated with property attributes such as the number of bedrooms and bathrooms, which is consistent with previous research (e.g., Boutsioukis et al., 2019; Lawani et al., 2019). Our findings reveal that additional bedrooms and bathrooms significantly increase listing prices, reflecting consumer preferences for spacious and well-equipped accommodations. Similarly, additional amenities like Wi-Fi and free parking were found to be positively correlated with higher prices. While the impact of individual amenities was modest, the cumulative effect of multiple amenities was an important factor in shaping consumer preferences, though each additional amenity was found to add only €1.5 to the average price. It is worth noting, however, that the number of amenities was found to account for only 5% of the variance in prices.

Finally, host characteristics, particularly the Superhost status and the length of presence on the platform, were also significant factors affecting listing prices. Listings offered by Superhosts were more expensive, which is consistent with Arvanitidis et al. (2020), who demonstrated that professional hosts leverage institutional trust mechanisms to charge more. This shows the value of reputation and trust in peer-to-peer accommodation markets, suggesting that hosts with established credibility can capitalize on their status to increase their revenue. While the price of Airbnb listings depended on accommodation type, the type of licence did not have much effect on the price distribution. Listings exempt from licensing requirements (e.g., due to specific legal exceptions or classifications) were found to be €10 less expensive than licensed properties, and unlicensed listings were €2 less expensive. These findings can help hosts and professional listing managers adjust pricing strategies based on property and licence types. For example, hosts offering shared rooms may want to reconsider their pricing strategy to remain competitive. Similarly, hosts whose properties are exempt from licensing requirements may need to change their pricing approach in order to prevent overpricing and losing bookings.

While review scores were positively associated with higher prices, their overall impact was modest. This is consistent with the view that review scores serve as a quality signal, influencing consumer decision-making but play a secondary role compared to structural and locational factors. These results are consistent with studies like Hong & Yoo (2020) and Chen & Bi (2022), which indicate that they have limited influence on pricing.

Overall, this study demonstrates the importance of listing characteristics in pricing decisions. Our findings can help hosts, professional listing managers, and policymakers in Greece improve their pricing strategies and rules for Airbnb listings.

6. Conclusion

The above study provides a comprehensive analysis of the factors influencing Airbnb pricing in Greece, the main ones being the listing's location, its internal characteristics, and host attributes. The analysis revealed statistically significant differences between urban and island regions, with listings located in island areas being considerably more expensive. Accommodation prices were also found to be affected by property and licence type, as well as host characteristics, particularly the Superhost status. Listing attributes, such as the number of bedrooms, bathrooms, and the number of amenities were also key price determinants, reflecting consumer preferences for well-equipped and spacious accommodations. Two specific amenities, namely Wi-Fi and free parking, were found to have a significant effect on the price. In other words, both hypotheses put forward at the start were confirmed.

The study offers actionable insights for hosts and policymakers. Hosts can optimise their pricing strategies by leveraging locational advantages based on regional pricing differences, enhancing property features by adding amenities to their listings, and building trust through positive reviews and professional management practices. Policymakers can use these findings to design targeted regulations that address regional disparities and promote sustainable growth in the short-term rental market.

CRediT Authorship Contribution Statement

Georgia Zouni: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, writing – review & editing; **Ioannis Katsanakis:** conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, writing – review & editing;

Athanasios Athanasiadis: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, writing – review & editing; **Myrsini Sofia Nika:** conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, writing – review & editing.

Declaration of Competing Interest

None.

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Wpływ różnych czynników na ceny noclegów oferowanych w Grecji za pośrednictwem serwisu Airbnb

Streszczenie. Celem artykułu jest analiza wpływu różnych czynników na ceny noclegów na platformie Airbnb. Opisane w artykule badanie jest oparte na danych dotyczących 31705 miejsc noclegowych oferowanych w czterech głównych regionach Grecji (Ateny, Saloniki, Kreta i południowe Morze Egejskie), które pojawiły się na platformie Airbnb w grudniu 2022 r. i zostały zarejestrowane przez Inside Airbnb. Autorzy zastosowali testy statystyczne i analizę regresji, aby zidentyfikować kluczowe czynniki wpływające na ceny. Wyniki analizy potwierdzają istnienie wyraźnych różnic w poziomie cen, które zależą od czynników zewnętrznych, takich jak region, w którym znajduje się dana oferta, czynników wewnętrznych miejsc noclegowych oraz cech gospodarza. Wyniki badania mogą pomóc gospodarzom oferującym noclegi, administratorom ofert i decydentom w dostosowywaniu strategii cenowych i przepisów do zmian zachodzącym na dynamicznym rynku Airbnb w Grecji.

Słowa kluczowe: gospodarka współdzielenia, czynniki determinujące ceny, Airbnb