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What drives apartment rental rates on Booking.com? A hedonic pricing approach

Co wpływa na stawki za wynajem apartamentu na Booking.com? Hedonistyczne podejście cenowe

Keywords:
sharing economy, rental rate determinants, Booking.com, quantile regression, random forest

Abstract: This study investigates the determinants of apartment rental rates listed on Booking.com across 25 Polish cities divided into 7 NUTS (Nomenclature of Territorial Units for Statistics) regions. Using web-scraped data, we analyze the impact of apartment characteristics, host attributes, location, and platform-specific features on rental rate levels. Particular attention is given to the role of affiliate program participation (Preferred, Preferred Plus), review ratings, language skills and location.

Quantile regression and random forest models are applied to account for rental rate heterogeneity. The results indicate that apartments affiliated with Booking.com programs command significantly higher rental rates. While multilingual descriptions particularly in English and German are positively associated with higher rental rates, Russian language availability shows a negative relationship. Additionally, although overall review scores are positively linked to rental rates, the value for money rating tends to be lower for more expensive apartments. The study contributes to the literature by extending pricing analysis beyond Airbnb and incorporating Booking.com-specific mechanisms, rarely addressed in prior research. Practical implications concern pricing strategies and platform design. Limitations include the cross-sectional nature of the data and potential selection bias in scraped listings. By addressing platform-specific pricing determinants, this research provides new insights into how online presentation and platform affiliation influence perceived apartment value in the digital short-term rental market.

Słowa kluczowe:
ekonomia współdzielenia, ceny apartamentów, determinanty cenowe, Booking.com, regresja kwantylowa, lasy losowe

Streszczenie: Niniejsze badanie analizuje determinanty stawek najmu apartamentów oferowanych na platformie Booking.com w 25 polskich miastach, podzielonych na 7 regionów NUTS (Nomenklatura Jednostek Terytorialnych do Celów Statystycznych). Wykorzystując dane pozyskane metodą web scrapingu, zbadano zależność cech apartamentu, znajomości języków przez gospodarza, lokalizacji oraz specyficznych funkcji platformy na poziom stawek najmu. Szczególną uwagę poświęcono uczestnictwu w programach afiliacyjnych (Preferred, Preferred Plus), ocenom recenzji oraz umiejętnościom językowym.

Zastosowano modele regresji kwantylowej oraz lasów losowych, aby zbadać heterogeniczność stawek najmu. Wyniki wskazują, że apartamenty uczestniczące w programach afiliacyjnych Booking.com osiągają istotnie wyższe stawki najmu. Choć opisy apartamentów w wielu językach zwłaszcza po angielsku i niemiecku są pozytywnie skorelowane z wyższymi stawkami najmu, znajomość języka rosyjskiego wykazuje relację negatywną. Dodatkowo, mimo że ogólna ocena apartamentu ma tendencję do wzrostu wraz z ceną, ocena stosunku jakości do ceny jest niższa dla droższych ofert.

Badanie wnosi wkład do literatury, rozszerzając analizy cenowe poza Airbnb i uwzględniając mechanizmy charakterystyczne dla Booking.com, które dotąd były rzadko badane. Praktyczne implikacje dotyczą strategii cenowych oraz zrozumienia specyfiki platformy. Ograniczenia badania obejmują przekrojowy charakter danych oraz potencjalną stronniczość wynikającą z selekcji ogłoszeń.

Podejmując temat specyficznych dla platformy determinant cenowych, niniejsze badanie dostarcza nowych wniosków na temat tego, w jaki sposób prezentacja online oraz afiliacja z platformą wpływają na postrzeganą wartość apartamentu w cyfrowym rynku wynajmu krótkoterminowego.

JEL:
L83, C21, R31, Z32, L86, D12

Introduction

Short-term rentals constitute a rapidly growing segment of the accommodation market, facilitated primarily by online platforms that connect property owners with temporary tenants. These platforms such as Airbnb, Booking.com, and Vrbo enable users to book private rooms, apartments, or entire homes for periods typically ranging from a single night to several weeks. While a considerable body of research has focused on Airbnb, far less is known about the rental rate determinants specific to Booking.com, despite its significant role in the global short-term rental ecosystem.

The aim of this study is to identify and empirically evaluate the main factors affecting apartment rental rates on the Booking.com platform. Understanding these deter-

minants is crucial for both researchers interested in platform economics and property owners seeking to optimize their pricing strategies. The analysis is based on a dataset covering 25 Polish cities divided into 7 NUTS (Nomenclature of Territorial Units for Statistics) regions, including 5,590 apartment listings and 26 variables obtained through web scraping using the Selenium library.

Booking.com and Airbnb differ in several key ways, which justifies the need for platform-specific research when analyzing short-term rental pricing. While Booking.com features a broad range of property types, including hotels, hostels, and guesthouses, this study focuses exclusively on apartments to maintain consistency and comparability of results. On Booking.com, apartments are more often managed by professional operators or property agencies, who typically rely on structured pricing models and standardized amenities. In contrast, Airbnb listings are usually managed by private individuals, which often results in more varied quality and more dynamic pricing practices influenced by host discretion and local demand fluctuations. Additionally, the platforms diverge in how they highlight listings and incentivize quality: Booking.com offers visibility-enhancing programs such as Preferred and Preferred Plus, while Airbnb distinguishes certain hosts through the Superhost program. Another notable difference lies in the presentation of listings, Booking.com provides more detailed descriptions of amenities and allows hosts to specify which languages they speak, potentially improving trust and communication between guests and hosts. Furthermore, Airbnb tends to emphasize personalized, residential-style stays, whereas Booking.com rentals, even among apartments, more closely resemble hotel-like offerings. These contrasts suggest that the determinants of rental rate may differ notably between platforms, making it important to analyze each within its own operational context.

This study makes a significant contribution to the literature on the determinants of apartment rental rates on online booking platforms, such as Booking.com. Specifically, the research analyzes new variables that have not been extensively explored in previous studies on apartment rentals on online platforms.

One of the key contributions of this study is the inclusion of variables related to affiliation on Booking.com, such as participation in the "Preferred" and "Preferred Plus" programs. These programs, offering higher visibility and promotion on the platform, may have an impact on rental rates, which has been incorporated into the analysis. Participation in these programs is considered a distinguishing feature, possibly indicating higher service quality and greater competitiveness among hosts. The results show that both programs positively affect the rental rate, with the effect being particularly strong for the "Preferred Plus" program, which suggests higher standards of accommodation offered. In addition to affiliation-based variables, the study also accounts for geographic differentiation by incorporating macroregional divisions within Poland. This allows for

the identification of spatial pricing patterns, offering insights into how location-based disparities influence apartment pricing in the short-term rental market.

Previous studies on rental rates in the sharing economy have predominantly focused on platforms such as Airbnb, which is a limitation, as these platforms differ significantly in various aspects from Booking.com, especially in terms of available accommodation types and customer demographics. This study expands the literature by examining rental rates on Booking.com, providing valuable insights into the rental rate determinants specific to this platform. The results indicate that factors such as the availability of additional services, location rating, and affiliation programs have different impacts on rental rates compared to findings from Airbnb studies. For instance, the results highlight the importance of location ratings, which may be especially relevant in the context of business travel or tourism, where location plays a key role.

The findings of this study have significant implications for both researchers and practitioners. For researchers, they offer new avenues for exploring rental rates on online platforms, emphasizing the importance of affiliation and language-related variables, which have been less frequently examined in the context of rental rates. Additionally, the application of quantile regression allows for a deeper understanding of rental rate variation across different market segments, providing a new methodological approach for studies on rental rates.

For practitioners, including property owners and platform managers, the results offer practical insights into factors influencing rental rates. For example, participation in the "Preferred" and "Preferred Plus" programs may represent an effective strategy for increasing rental rates, particularly for properties offering a higher level of service. Hosts may also find it valuable to consider how proficiency in foreign languages (such as English, German, or Ukrainian) affects the attractiveness of their listings, as this could help attract specific tourist groups.

In summary, this study introduces new variables into the analysis of rental rates on Booking.com, expands the existing literature on platforms like Airbnb, and provides practical insights for hosts and researchers. It highlights the importance of affiliation programs, location, and language in determining rental rates and offers guidance for adapting offerings to customer expectations.

The following research hypotheses are formulated:

- **H1 (Affiliation hypothesis):** Apartments participating in affiliate programs such as *Preferred* or *Preferred Plus* achieve higher rental rates compared to non-affiliated listings.

  Rationale: Affiliate badges may serve as a signal of quality or increased platform visibility, allowing hosts to charge premium rental rates [Wang, Nicolau, 2017; Zhao et al., 2023].

- **H2 (Language hypothesis):** Apartments whose hosts provide information or services in international languages (e.g., English, German, Russian, or Ukrainian) are associated with higher rental rates.
  Rationale: Multilingual communication enhances accessibility for foreign guests and can increase perceived professionalism, thereby justifying higher pricing [Chang, Li, 2020].
- **H3 (Review hypothesis):** Guest ratings on Booking.com are significantly associated with apartment rental rates. Specifically, *location rating* is expected to have a positive effect, while *value-for-money rating* is expected to be negatively related to rental rate.
  Rationale: Positive location assessments may signal convenience and prestige, whereas low value-for-money scores may reflect unmet guest expectations in higher rental rates [Chen, Xie, 2017; Gibbs et al., 2017].
- **H4 (Regional differentiation hypothesis):** Apartments located in Poland's Masovian macroregion are associated with higher rental rates compared to apartments in other macroregions.
  Rationale: The Masovian region, which includes the capital city Warsaw, likely reflects higher demand, economic activity, and tourism traffic, which may drive up accommodation rental rates.

The remainder of the article is organized as follows. Section 2 presents a review of the relevant literature and outlines gaps addressed by the current study. Section 3 describes the methodology, data collection process, and variables. Section 4 presents the empirical results and hypothesis testing. The final section discusses key findings, limitations, and potential avenues for future research.

Literature review

The short-term rental (STR) market has experienced rapid growth in recent years, driven by digital platforms such as Airbnb and Booking.com. This growth has been accompanied by a rise in academic interest, especially in understanding the determinants of rental pricing. The literature in this area has expanded significantly since around 2015, but it is still characterized by several important limitations. Notably, research tends to focus almost exclusively on Airbnb, despite structural and operational differences between platforms. Furthermore, much of the literature lacks coherent theoretical grounding, and few studies systematically analyze how platform-specific or regional characteristics influence pricing. This literature review aims to provide a structured overview of the most relevant findings, focusing on three broad categories of rental rate determinants: reputation, location, and amenities (see Table 1). It concludes by highlighting existing research gaps and justifying the design of the present study.

Property and Host Characteristics

Research consistently shows that property and host characteristics including apartment size (number of bedrooms, total surface area), availability of key amenities (kitchen, private bathroom, air conditioning, Wi-Fi, television, balcony), and house rules (smoking and pet policies) exert a strong influence on short-term rental rates [Wang, Nicolau, 2017; Voltes-Dorta, Sánchez-Medina, 2020; Jiang et al., 2022]. Larger apartments with more bedrooms and bathrooms command higher rates, while high-demand amenities such as Wi-Fi and air conditioning typically justify rental rate premiums [Dudás et al., 2020]. Evidence for features like a television or a balcony is mixed, some hotel-based hedonic studies find positive effects [Chen, Rothschild, 2010; Chau et al., 2004], but Airbnb analyses often report insignificant results [Solano-Sánchez et al., 2021; Santos et al., 2020]. Similarly, strict house rules (e.g., no smoking or no pets) do not uniformly affect rental rates, suggesting that guests trade off convenience against flexibility in different market segments [Chang, Li, 2020]. Hosts' professional status whether individually managed or operated by agencies using revenue-management tools also shapes pricing strategies, with professionally managed listings often following more standardized rate plans [Schamel, 2012].

Location is another determinant of STR pricing and has been widely studied using two dominant approaches: as proximity to key landmarks such as the city center or public transportation [Zhao et al., 2023; Wang, Nicolau, 2017], or by comparing listings across different cities or tourism regions [Gyódi, Nawaro, 2021; Zhang et al., 2017]. The former focuses on intra-city rental rate gradients, while the latter captures broader regional disparities. This study adopts the proximity-based approach measuring distance from the city center and nearest public transport as a continuous, spatial variable. Moreover, it addresses a notable gap in the literature by explicitly analyzing regional differences within a single country context, namely Poland. While prior work has primarily concentrated on individual metropolitan areas (often limited to capital cities), this research expands the scope by comparing pricing patterns across multiple Polish cities, offering a more granular understanding of spatial heterogeneity within national markets.

When it comes to host communication an interesting characteristic is multilingual communication: by advertising proficiency in multiple languages, hosts reduce information asymmetry and appeal to international travelers. Multilingual communication, although underexplored, may play a critical role in the pricing of STR properties, especially in international markets with diverse tourist profiles [Chang, Li, 2020]. Research has suggested that language accessibility can attract international guests and increase booking conversion rates. This factor is particularly relevant in countries like Poland, where the tourism market includes both domestic and international visitors, and language barriers may impact a guest's decision-making process.

However, a notable discrepancy in the literature is that while language skills are often seen as a positive feature in the context of international tourism, their direct impact on pricing remains unclear. While some studies suggest a positive relationship between multilingualism and higher rental rates, other research has indicated that the effect may be minimal if the host's language proficiency does not align with the tourist's primary language. This calls for further exploration, particularly on platforms like Booking.com, where multilingual communication may be crucial for attracting a broader guest base.

Online Reputation and Guest Ratings

Online reputation and guest ratings are widely recognized as crucial factors influencing the pricing of STRs. Higher average ratings allow hosts to charge higher rental rates [Zervas et al., 2015], but recent studies have highlighted nuances in this relationship. For example, location and cleanliness ratings have been found to have a stronger effect on rental rate than overall satisfaction scores [Cheng, Jin, 2019; Abrate, Viglia, 2019]. This suggests that guests may prioritize specific attributes when determining willingness to pay, which may be platform-dependent. The importance of "value for money" ratings, often negatively associated with rental rate, indicates that guests may have a greater rental rate sensitivity, particularly when accommodations are seen as offering less value compared to their rental rate [Chen, Xie, 2017].

A key contradiction arises when comparing Airbnb and Booking.com in terms of guest ratings. While both platforms use ratings to signal quality, the weighting of different types of ratings may differ. On Airbnb, overall satisfaction is highly emphasized, while on Booking.com, specific ratings such as location and cleanliness might carry more weight. This discrepancy is worth investigating, as it could affect how hosts on these platforms set their rental rates based on guest feedback.

Platform-Specific Affiliation and Badges

Affiliation badges like Airbnb's "Superhost" status or Booking.com's "Preferred Partner" or "Prefered Plus" badge serve as signals of quality that may justify rental rate premiums [Teubner et al., 2017; Dogru et al., 2020]. However, while the effect of Airbnb's Superhost status on rental rate has been well-documented, the influence of Booking.com's affiliation programs on pricing remains underexplored. Booking.com hosts who meet certain performance criteria, such as high average guest ratings and booking frequency, may apply for these designations. In return for paying higher commission fees to the platform, hosts benefit from greater visibility and enhanced ranking in search results. Booking.com claims that listings in the Preferred Partner Program can gain up to 65% more visibility and receive, on average, 20% more bookings, while those in the

Preferred Plus Program may see visibility increases of up to 60% and booking gains of up to 30%. These programs represent commercially structured signals of trust and popularity that are prominently displayed to potential guests, functioning similarly, though not identically, to Airbnb's "Superhost" badge. Despite their operational significance, Booking.com's affiliate programs have not yet been systematically analyzed in the academic literature, particularly with respect to their relationship with pricing. This gap presents a valuable opportunity for further investigation, as the programs may convey quality and visibility benefits that influence a host's ability to charge premium rental rates. The present study explicitly includes these affiliate statuses as explanatory variables, helping to address this omission.

Table 1. Literature Overview by Category of Rental rate Determinants

Category	Determinant	Effect on Rental rate	Sources
Host-related	Language proficiency	Positive	Chang & Li [2020]; this study
	Number of reviews	Mixed (positive/negative)	Wang & Nicolau [2017]; Cai et al. [2019]; Ert et al. [2016]
	Review scores (e.g., value, location)	Mixed (positive/negative)	Chen & Xie [2017]; Gibbs et al. [2017]; Voltes-Dorta & Sánchez-Medina [2020]
	Superhost / Affiliation status	Positive	Wang & Nicolau [2017]; Zhao et al. [2023]; this study
Location-related	Distance to city center	Negative / insignificant	Schamel [2012]; Zhang et al. [2017]; Gyódi & Nawaro [2021]
	Proximity to public transport	Mixed (positive/negative)	Voltes-Dorta & Sánchez-Medina [2020]; Chang & Li [2020]
Platform-related	Booking.com Preferred / Plus	Positive	this study
	Airbnb Superhost program	Positive	Wang & Nicolau [2017]; Chang & Li [2020]; Zhao et al. [2023]
Amenity-related	Wi-Fi	Positive	Wang & Nicolau [2017]; Chen & Rothschild [2010]
	Kitchen	Insignificant / mixed	Chang & Li [2020]; Santos et al. [2020]
	Balcony	Mixed / insignificant	Chau et al. [2004]; Solano-Sánchez et al. [2021]
	Air conditioning	Positive	Wang & Nicolau [2017]; Chen & Rothschild [2010]
	Smoking policy	Non-smoking → higher rental rate	Dudás et al. [2020]
	Pets allowed	Insignificant	Dudás et al. [2020]; Wang & Nicolau [2017]

Source: own elaboration.

Methodological Approaches in STR Pricing Research

The short-term rental (STR) pricing literature has primarily employed hedonic pricing models, most commonly ordinary least squares (OLS) regression, to estimate the effect of various property, host, and location characteristics on rental rates. This approach is valued for its transparency and interpretability and has been widely applied across different STR studies [e.g., Voltes-Dorta, Sánchez-Medina, 2020; Chen, Xie, 2017; Ert et al., 2016; Solano-Sánchez et al., 2021; Schamel, 2012]. However, OLS assumes constant marginal effects and struggles with nonlinearities and multicollinearity, especially when analyzing high-dimensional feature sets like amenities and guest ratings.

To overcome these limitations, several studies have introduced quantile regression (QR), which allows for heterogeneity in variable effects across the rental rate distribution. This method can highlight differences in determinants for budget versus premium listings. For instance, Wang & Nicolau [2017] and Dudás, Kovalcsik, Vida, et al. [2020] used quantile regression to show how the influence of some features intensifies at higher rental rate quantiles. Despite these advantages, QR is still underused in the STR context.

Some researchers have integrated geographically weighted regression (GWR) to account for spatial heterogeneity in pricing drivers, which is particularly relevant for urban STR markets where the value of location-based features can vary widely. Notable examples include Zhao, Wu, Chen, et al. [2023] and Zhang, Chen, Han, et al. [2017], who combine OLS or generalized linear models (GLM) with GWR to spatially map rental rate determinants.

More recently, machine learning techniques have been introduced, especially tree-based methods like Random Forest (RF) and Support Vector Regression (SVR), which can flexibly model nonlinear interactions and automatically rank feature importance. Studies such as Chang & Li [2020] and Jiang, Zhang, Xianting, et al. [2022] have applied RF to explore complex pricing patterns in STR data. Nevertheless, these approaches often trade off interpretability for predictive accuracy and are not always suitable for inference.

In addition, spatial econometric models like the Spatial Durbin Model (SDM) have been used to explicitly account for autocorrelation between nearby listings, as demonstrated by Gyódi & Nawaro [2021].

Overall, OLS remains the dominant approach in the literature, while the combination of quantile regression, machine learning, and spatial models is relatively rare but growing. To date, few studies apply these methods to Booking.com data specifically, as most research has focused on Airbnb, highlighting a methodological and platform-specific gap that this study aims to address by combining quantile regression and Random Forest.

Research Gap

While many determinants of STR rental rates have been investigated for Airbnb, research on Booking.com remains scarce. Few studies include Booking-specific attributes such as affiliation programs, Booking's rating categories, or language accessibility. Moreover, prior studies tend to focus on single cities or regions, limiting generalizability.

This study addresses these gaps by focusing on Booking.com listings in Poland, using a combination of quantile regression and Random Forest methods to better capture heterogeneity in rental rate determinants. It contributes insights into the effects of multilingualism and platform-specific affiliation programs on pricing, while also exploring regional variation across multiple Polish cities thus offering a more comprehensive and context-sensitive understanding of STR pricing dynamics.

Method

Data Source and Collection Process

Booking.com is one of the largest global platforms for booking accommodation, offering a wide range of lodging options, including hotels, apartments, guesthouses, and cottages. Each listing provides extensive information such as a description of the property, photos, pricing, availability, amenities, and guest ratings. Users can filter results based on multiple criteria and sort listings by rental rate, popularity, distance, or rating, making the platform a rich source of structured user-generated data.

The dataset for this study was compiled using a custom Python web scraping script developed with the Selenium library. The script targeted apartment listings on Booking.com across the 25 Polish cities with the highest number of apartment listings, as determined at the time of scraping. For each city, the search was conducted for a standardized booking scenario: two adults, one room, with a one-night stay from January 8 to January 9, 2024. The "apartments" filter was applied to ensure consistency in accommodation type.

To capture all available listings, the script simulated user interactions, including clicking on individual listings, and sequentially scraped each listing's details. Booking.com limits search results to a maximum of 1,000 listings per city. To overcome this constraint in larger cities such as Warsaw and Kraków, the scraping process was repeated separately for each district. It is important to note that Booking.com sometimes displays accommodations located just outside the specified city, potentially creating overlaps between listings in neighboring cities. However, no duplicate entries were observed in the final dataset. To standardize pricing across listings, rental rate per person was calculated,

as Booking.com occasionally displays listings suitable for more than two guests, even under a two-person search query. Several filtering steps were applied during the data cleaning process. Only listings with at least one review and with available ratings in the relevant subcategories used in the analysis (e.g., cleanliness, location, value for money) were retained. Incomplete entries were addressed systematically: for apartment characteristics expressed as binary variables (e.g., availability of a balcony, kitchen, or Wi-Fi), missing values were interpreted as the absence of the feature (i.e., coded as 0). Listings that lacked information on essential attributes, such as surface area, were excluded from the analysis. Finally, each listing was assigned to one of the NUTS-1 regions of Poland based on the city of origin. To explore whether regional differences in rental rates followed a spatial pattern, Moran's I test was applied using average log rental rates across NUTS-1 regions. Spatial weights were defined using queen contiguity (shared borders). The test result (Moran's $I = -0.58$, $p = 0.84$) indicated no significant spatial autocorrelation, suggesting that similar prices do not tend to cluster in neighboring regions. Initially, 5,985 listings were recorded. After excluding observations with missing values particularly lacking guest reviews or key apartment characteristics the final dataset included 5,590 observations.

Description of Variables

Table 2 provides an overview of the variables used in the econometric models.

Table 2. Variables Included in the Analysis

Category	Variable Name	Definition
Explained variable	Rental rate	Rental rate per person for the cheapest room in the listing (in PLN)
Location	Distance from center	Distance from city center (in meters)
	Proximity to public transport	Distance to the nearest public transport stop (in meters)
Affiliate programs	Preferred	=1 if host participates in Booking's Preferred Partner program
	Preferred Plus	=1 if host participates in Preferred Partner Plus program
Reputation	Number of reviews	Total number of guest reviews for the listing
	Rating: Value for money	Guest evaluation of value for money (scale 1–10)
	Rating: Location	Guest evaluation of location (scale 1–10)
Surface	Area	Apartment surface area (in square meters)
Amenities	TV	=1 if apartment has a TV
	Wi-Fi	=1 if apartment has Wi-Fi

cont. Table 2

Category	Variable Name	Definition
	Kitchen	=1 if apartment includes a kitchen
	Balcony	=1 if apartment has a balcony
	Bathroom	=1 if apartment has a private bathroom
	Air conditioning	=1 if apartment has air conditioning
Languages spoken	English	=1 if host speaks English
	German	=1 if host speaks German
	Russian	=1 if host speaks Russian
	Ukrainian	=1 if host speaks Ukrainian
Rules	Smoking allowed	=1 if smoking is permitted in the apartment
	Pets allowed	=1 if pets are allowed
NUTS1 Region (reference: Masovian Macroregion)	Central Macroregion	=1 if located in the Central Macroregion
	Eastern Macroregion	=1 if located in the Eastern Macroregion
	North-Western Macroregion	=1 if located in the North-Western Macroregion
	Northern Macroregion	=1 if located in the Northern Macroregion
	South-Western Macroregion	=1 if located in the South-Western Macroregion
	Southern Macroregion	=1 if located in the Southern Macroregion

Note: Variables such as overall rating, cleanliness rating, comfort rating, staff rating, and facility rating were initially considered. However, due to high multicollinearity (correlation coefficients above 0.85), these were excluded from the final model to improve estimation robustness.

Source: own elaboration.

To provide initial insights, descriptive statistics (Annex, Table A1), histograms, and boxplots were examined. For continuous variables, Pearson correlations with rental rate were calculated. For binary variables, median rental rates across subgroups were compared using the Wilcoxon rank-sum test to assess potential differences.

Research Methodology

Previous research on short-term rental (STR) pricing has mostly used ordinary least squares (OLS) regression because it is easy to understand and widely used [Zhao et al., 2023; Voltes-Dorta, Sánchez-Medina, 2020]. However, OLS only estimates the average effect of each variable and assumes a simple linear relationship, which can miss important differences across rental rate levels and fail to capture complex patterns. To address these limitations, this study uses both quantile regression and Random Forest models. Quantile regression, introduced by Koenker and Bassett [1978], allows for estimating how variables affect different parts of the rental rate distribution, such as low, middle, or high-rental rated listings. This method is more robust to outliers and gives deeper insight into how different market segments respond to factors like location or amenities

[Widłak, Nehrebecka, 2011; Nehrebecka, Widłak, 2012]. At the same time, the Random Forest method is a machine learning approach based on many decision trees it can model complex and nonlinear relationships without needing strong assumptions about the data. It also helps identify which variables are most important for predicting rental rate. By combining these two methods, the study gains both detailed understanding of how variables influence rental rates at different levels and strong predictive performance.

Results

Estimation Results and Diagnostics

To estimate the relationship between the explanatory variables and the dependent variable quantile regression models, as previously described, were applied (see Table 3).

Quantile regression estimation was performed for three quantiles: 0.25, 0.5, and 0.75 (marked as Q25, Q50, and Q75, respectively). The bootstrap method was used to estimate standard errors, involving drawing observations from the database and estimating the model for a given quantile. This process was repeated 500 times, and the standard deviation of the estimators from the drawn samples was then calculated. The use of this method makes the estimation more robust to heteroscedasticity.

Table 3. Results of Estimation: Quantile Regression

Category	Variable	Quantile regression		
		Q25	Q50	Q75
Location	Distance from the center	0.00001 (0.000004)	–0.00002 (0.000004)	–0.00005 (0.000003)
	Proximity to public transport	0.00002*** (0.00001)	0.00001 (0.00001)	0.00002*** (0.00001)
Affiliate Programs	Preferred	0.1634*** (0.0152)	0.1942*** (0.0146)	0.1578*** (0.0137)
	Preferred plus	0.1838*** (0.0286)	0.1522* (0.0802)	0.2788*** (0.0245)
Reputation	Number of reviews	–0.0001*** (0.00001)	–0.0001*** (0.00001)	–0.0001*** (0.00002)
	Rating value for money	0.0169* (0.0088)	0.0016 (0.0102)	–0.0446*** (0.0113)
	Location rating	0.0661*** (0.0118)	0.0653*** (0.0127)	0.0673*** (0.0129)
-	Surface	0.002*** (0.0005)	0.0041*** (0.0004)	0.007*** (0.0005)

cont. Table 3

Category	Variable	Quantile regression		
		Q25	Q50	Q75
Amenities	TV	0.0721** (0.0281)	0.0117 (0.0315)	0.0226 (0.0138)
	Wifi	0.0423*** (0.012)	0.0514*** (0.0156)	0.0403** (0.0174)
	Kitchen	0.0102 (0.0112)	–0.0039 (0.012)	–0.0488*** (0.0149)
	Balcony	0.0365*** (0.0118)	0.0503*** (0.012)	0.0548*** (0.0119)
	Bathroom	0.046*** (0.0141)	0.0332** (0.0148)	0.0107 (0.0165)
	Air conditioning	0.1225*** (0.0132)	0.1075*** (0.0122)	0.0948*** (0.0135)
Languages	English	0.0268* (0.0163)	0.0126 (0.0185)	0.0565*** (0.0219)
	German	0.0364** (0.0173)	0.0465** (0.019)	0.1012*** (0.0174)
	Russian	–0.0717*** (0.0148)	–0.0801*** (0.0147)	–0.0862*** (0.0172)
	Ukrainian	0.0607*** (0.0204)	0.0614*** (0.0221)	0.1048*** (0.0246)
Rules	Smoking	–0.01 (0.0233)	–0.0508** (0.0241)	–0.138*** (0.0269)
	Animals	–0.0195* (0.0115)	–0.0132 (0.0119)	–0.0311*** (0.0111)
NUTS1 Region	Central Macroregion	–0.2757*** (0.0228)	–0.3358*** (0.0253)	–0.0311*** (0.0111)
	Eastern Macroregion	–0.3092*** (0.0408)	–0.3172*** (0.0257)	–0.3468*** (0.0205)
	North-Western Macroregion	–0.1518*** (0.023)	–0.1774*** (0.0238)	–0.349*** (0.0328)
	Northern Macroregion	–0.2735*** (0.0201)	–0.3141*** (0.0179)	–0.1216*** (0.0271)
	South-Western Macroregion	–0.2076*** (0.0335)	–0.1802*** (0.0193)	–0.2449*** (0.0222)
	Southern Macroregion	–0.175*** (0.0256)	–0.1698*** (0.0216)	–0.1955*** (0.0234)
-	Constatnt	3.5031*** (0.1095)	4.1828*** (0.1152)	–0.0764*** (0.0203)
Number of observations		5590	5590	5590

Note: For quantile regression, standard errors were estimated using the bootstrap method with 500 replications. * – significance level 0.1, ** – significance level 0.05, *** – significance level 0.01.

Source: own elaboration.

To assess the model specification, a link test was performed separately for each quantile. This test involves regressing the dependent variable on the fitted values and their squared terms to detect possible misspecification. At the 10% significance level, the fitted values were statistically significant (p-values: 0.08 for Q25, 0.09 for Q50, and 0.04 for Q75), while the squared terms were not significant (p-values: 0.69, 0.36, and 0.83, respectively). This indicates that there is no evidence of misspecification in the functional form, as the significant fitted value confirms model relevance, and the insignificance of its square suggests no omitted nonlinearity. The next statistical test performed was the Wald test, which was used to assess whether the differences in the effect of explanatory variables on the dependent variable are significant across different quantiles of the model. This allows for analyzing the relationship between independent variables and rental rate in individual market segments.

The Random Forest model was implemented using the built-in out-of-bag (OOB) validation mechanism, which provides an internal estimate of prediction error without the need for cross-validation. The model was trained using 1,000 decision trees, each limited to a maximum of 50 terminal nodes (maxnodes = 50). At each split, 5 variables were randomly selected as candidates (corresponding to the square root of the 27 available predictors). To assess predictive performance, root mean squared error (RMSE) and mean absolute error (MAE) were computed on both training and test datasets. Importantly, these metrics were calculated using rental rates in their original scale (not logarithmic). The training RMSE was 89.12 PLN and MAE was 47.06 PLN, while the test RMSE reached 108.40 PLN and MAE was 54.96 PLN. The relatively small increase in error between training and test sets suggests that the model does not suffer from overfitting and generalizes well to unseen data.

Variable importance was evaluated using the %IncMSE (percent increase in mean squared error) measure (see Table 4). This metric quantifies the relative importance of each predictor by measuring the increase in prediction error when the variable's values are randomly permuted. Higher values indicate a stronger contribution to model accuracy.

Table 4. Results of Estimation: Random Forest

Category	Variable	%IncMSE
Location	Distance from the center	8,2806
	Nearest means of transport	8,0305
Affiliate Programs	Preferred	25,9390
	Preferred plus	4,2951
Reputation	Number of reviews	24,6779
	Rating value for money	5,8573
	Location rating	15,1290

cont. Table 4

Category	Variable	%IncMSE
-	Surface	22,9610
Amenities	TV	4,3892
	Wifi	2,8019
	Kitchen	3,3868
	Balcony	11,4438
	Bathroom	6,8613
	Air conditioning	18,6020
Languages	English	1,9007
	German	6,8311
	Russian	5,2071
	Ukrainian	2,8732
Rules	Smoking	0,0940
	Animals	5,3760
NUTS1 Region	Central Macroregion	8,3943
	Eastern Macroregion	11,4641
	Masovian Macroregion	18,5634
	North Western Macroregion	7,0619
	Northern Macroregion	15,1244
	South Western Macroregion	2,1854
	Southern Macroregion	3,7414

Source: own elaboration.

Verification of Research Hypotheses

Hypothesis 1: *The relationship between affiliate program participation and rental rate*

The first hypothesis posited that participation in the Preferred and Preferred Plus programs would be positively related to rental rate. Quantile regression estimates indicate that both "Preferred" and "Preferred Plus" statuses are significantly associated with higher rental rates across all examined quantiles (25th, 50th, and 75th percentiles). For example, the Preferred status is linked to rental rate increases of approximately 16% to 19% across quantiles, all highly statistically significant. The effect of the Preferred Plus program is also consistently positive, reaching nearly 28% at the upper end of the distribution. Wald test results suggest that the impact of affiliate program status is not uniform across the rental rate distribution: for Preferred listings, the differences

between Q25–Q50 and Q50–Q75 are significant, implying that the rental rate premium becomes more pronounced in higher quantiles. For Preferred Plus, the strongest contrast appears between Q25 and Q75, suggesting this status may be especially valuable in the upper segment of the market. This pattern is further evident in the graphs of parameter estimates (Annex, Fig. 1A, part A), where the Preferred Plus variable shows greater significance in higher quantiles, indicating that apartments participating in this program are able to command higher rental rates, particularly in the premium segment of the market.

These findings are partially echoed by the Random Forest results. The Preferred variable has the highest importance score (%IncMSE = 25.94), indicating a strong predictive relationship with rental rate. In contrast, the Preferred Plus variable shows a much lower importance score (4.30), suggesting its influence is more limited or possibly interacts with other variables in a more complex way. Overall, the combined evidence from both models supports the hypothesis, particularly for the Preferred program, while the effect of Preferred Plus appears more variable depending on the method and rental rate segment considered.

Hypothesis 2: *The relationship between language proficiency and rental rate*

The second hypothesis investigated the relationship between language proficiency and apartment rental rates. The results show that knowledge of Russian is negatively associated with the rental rate, which is unexpected and requires further investigation, as this negative effect is observed across the entire distribution. In contrast, knowledge of English, German, and Ukrainian is positively associated with rental rate, with significant differences for German and Ukrainian at higher rental rate quantiles. This suggests that German-speaking guests may have a higher willingness to pay for accommodation, likely due to the higher purchasing power and specific customer preferences of German-speaking tourists. The positive relationship with Ukrainian also aligns with expectations, as it could reflect the growing demand from Ukrainian-speaking tourists. The graphs of the estimated coefficients (Annex, Fig. 1A, part B) confirm these trends, showing a positive upward shift for German and Ukrainian while stable coefficients for Russian and English. These findings align with the Random Forest variable importance rankings, where German and Russian ranked highest among language variables in %IncMSE (6.83 and 5.21 respectively), indicating they are relevant for rental rate prediction, although to a lesser degree than affiliate program indicators. These findings challenge the hypothesis of a purely positive relationship between language proficiency and rental rate and underscore the need for further research into the negative effect of Russian proficiency.

Hypothesis 3: *The relationship between guest ratings and rental rate*

The third hypothesis concerned the significance of guest ratings, specifically location and value for money ratings. The results show a significant positive relationship between location rating and rental rate, consistent with the literature. However, the value for money rating exhibits a negative relationship with rental rate, suggesting that as the rental rate increases, guests may perceive the value as less proportional to the cost, even if the apartment offers high standards and amenities. This aligns with customer expectations, where higher-rental rated apartments often have higher service expectations. For less expensive apartments, even a standard offering may seem good value, leading to higher satisfaction and better ratings. The interquantile differences for location ratings were significant between Q25 and Q50, while the differences for the quality/rental rate ratings were significant between all estimated quantiles. Graphs (Annex, Fig. 1A, part C) show a noticeable negative relationship for value for money, while location ratings display an initial increase before decreasing in higher quantiles. These findings provide strong support for the hypothesis, indicating that guest ratings play a crucial role in shaping apartment rental rates and offer valuable insights for hosts.

The Random Forest results reinforce these findings: among the reputation-related variables, location rating (15.13) and value for money rating (5.86) shows high predictive power, with location rating ranking among the top predictors overall. This underscores the importance of perceived location quality in rental rate determination. Together, these findings provide strong support for the hypothesis, indicating that guest ratings play a crucial role in shaping apartment rental rates and offer valuable insights for hosts.

Hypothesis 4: *Regional differentiation hypothesis*

The fourth hypothesis examined regional differentiation, positing that apartments located in Poland's Masovian macroregion are associated with higher rental rates compared to those in other macroregions. The quantile regression results strongly support this hypothesis. Using the Masovian region as the reference category, all other regions showed significantly lower coefficients across the 25th, 50th, and 75th percentiles. The largest negative differences were observed for the Central and North-Western macroregions, indicating substantial regional rental rate disparities in the short-term rental market. The Random Forest model also supports these findings, assigning the highest importance score to the Masovian region (18.56), followed by the Northern (15.12) and Eastern (11.46) macroregions. In contrast, the South-Western and Southern regions had the lowest importance values, suggesting that location in those areas contributes less to rental rate prediction. Together, these results provide strong empirical support for the

hypothesis, demonstrating that being located in the Masovian microregion, likely due to its concentration of demand, tourism appeal, and higher urbanization is associated with significantly higher short-term rental rates.

Control Variables and Additional Analysis

The rest of the variables were treated as control variables. Distance from the center showed to be insignificant. For the proximity to public transport, a positive relationship with rental rates was observed in lower quantiles, consistent with previous research. The number of reviews negatively correlated with rental rate, reflecting that cheaper apartments tend to attract more reviews, a finding consistent with existing studies. The surface area of apartments showed a strong positive relationship with rental rate, with significant differences across quantiles, especially at higher rental rate points. This confirms previous findings that larger apartments command higher rental rates, particularly in premium segments. As for amenities, variables like Wi-Fi, bathrooms, air conditioning, and balconies positively influenced rental rates, while a kitchen was found to reduce rental rate at higher rental rate quantiles, potentially indicating a standard feature in higher-end apartments. The presence of a television had no significant relationship with rental rate, suggesting it is perceived as a basic, expected feature. Finally, rules such as smoking and pets showed a negative impact on rental rate, which aligns with customer preferences for non-smoking and pet-free environments.

Comparison with Airbnb Studies

The results of this study offer valuable insights into the pricing mechanisms of short-term rental apartments on Booking.com and allow for comparison with previous research focused on the Airbnb platform. In general, the direction and significance of the determinants identified in this study are consistent with patterns observed in the literature on Airbnb, but important differences emerge due to platform-specific mechanisms and user behaviors.

Affiliate Programs and Badges:

The finding that participation in affiliate programs such as Preferred and Preferred Plus is positively associated with rental rates on Booking.com mirrors similar evidence for Airbnb's Superhost status. For example, Teubner et al. [2017] and Dogru et al. [2020] demonstrated that Airbnb Superhosts enjoy rental rate premiums, interpreted as quality signals that enhance trust and visibility. On Booking.com, the Preferred Plus program in particular appears to serve a similar signaling function. However, the

layered structure of Booking.com's affiliation system (e.g., multiple levels such as Preferred and Preferred Plus) creates greater pricing stratification compared to Airbnb, where the Superhost badge functions as a binary status.

Online Reputation and Reviews:

Consistent with research on Airbnb [e.g., Zervas et al., 2015; Cheng, Jin, 2019], this study found that guest ratings significantly affect rental rates. In both platforms, higher ratings for location are associated with higher rents, whereas value-for-money ratings tend to have a negative or non-significant effect, possibly reflecting higher guest expectations for expensive listings. However, while previous Airbnb studies focused heavily on overall ratings, the results here suggest that specific sub-ratings (e.g., location, value for money) offer more nuanced insights, particularly in the Booking.com context where guests tend to be more heterogeneous (including both leisure and business travelers).

Language Proficiency of Hosts:

This study finds that multilingualism is positively associated with higher rental rates on Booking.com (especially for English and German), echoing findings from Chang & Li [2020] for Airbnb. However, the observed negative association for Russian language proficiency is less commonly addressed in Airbnb literature and may reflect region-specific guest preferences or sociopolitical factors affecting demand – an aspect more relevant in the Booking.com context given its broader geographic and demographic reach.

Regional differences:

This study confirms that apartments located in Poland's Masovian macroregion are associated with significantly higher rental rates compared to those in other regions, suggesting the presence of pronounced spatial rental rate disparities within the country. While Airbnb studies such as Wang & Nicolau [2017] and Zhang et al. [2017] have highlighted location as a key determinant of rental rate, fewer have explicitly explored regional rental rate differentiation using standardized territorial classifications such as NUTS. The current study addresses this gap by applying a macroregional framework (NUTS1), revealing systematic pricing differences not only between cities but across broader geographical areas. The findings suggest that, on Booking.com, rental rates may be more strongly tied to regional economic or touristic development levels than is typically emphasized in Airbnb literature, which often focuses on neighborhood-level or city-specific dynamics.

Professionalization of Hosts:

While Airbnb studies have shown that professional hosts (those managing multiple listings) tend to charge higher rental rates [Liang et al., 2017], Booking.com has historically catered more to professional property managers and hotels. This structural difference means that host professionalism is more normalized on Booking.com, potentially reducing its explanatory power as a rental rate determinant compared to Airbnb, where the distinction between amateurs and professionals is more salient.

In summary, the determinants of rental rates on Booking.com are broadly aligned with those identified in Airbnb studies, but platform-specific differences in host composition, affiliation systems, and user expectations lead to some divergence in effects. These findings highlight the importance of platform context when interpreting rental rate dynamics in the short-term rental market.

Limitations

While the findings presented in this study provide valuable insights into the determinants of apartment rental rates on Booking.com in Polish cities, there are several limitations that must be acknowledged.

First, the analysis is based on data collected from a single online platform, which may not fully represent the entire accommodation market in these cities. Rental rates and features listed on Booking.com may differ from those available through other platforms, such as Airbnb or direct bookings through hotel websites, which could lead to some biases in the results. Furthermore, the study focused only on the quantitative data available on the platform, and factors such as subjective guest experiences or the local economic context were not directly captured, potentially limiting the understanding of deeper drivers of rental rate variation.

Second, the use of quantile regression, while providing insights into different segments of the rental rate distribution, may also present challenges. The robustness of results could be influenced by the heterogeneity of the data, especially when dealing with a large sample of observations. Variability in apartment characteristics, guest preferences, and local market conditions may contribute to differences that are not entirely accounted for by the variables included in the model.

Third, while this study highlights significant relationships between variables like language proficiency and apartment rental rates, the analysis does not explore the causality of these relationships. For instance, the negative association between Russian language proficiency and rental rate, though intriguing, requires further investigation to understand whether it is a result of other underlying factors, such as regional economic differences or the specific characteristics of Russian-speaking tourists. A more

in-depth, causal analysis, perhaps incorporating a longitudinal approach, would be necessary to clarify these dynamics.

Additionally, while the data used in the study is relatively comprehensive, it is limited to the period covered by the available data (2024), meaning that the effects of more recent trends or changes in consumer behavior due to global shifts, are not fully captured. Future research could extend this analysis by considering more up-to-date data or even exploring how recent external shocks have influenced the accommodation pricing model.

Lastly, the study did not account for potential spatial dependencies in the data, such as the influence of nearby competitors on pricing decisions or neighborhood-level effects on apartment rental rates. Incorporating spatial econometrics or geographic information system (GIS) techniques in future studies could provide a more nuanced understanding of how location-specific factors affect pricing dynamics.

These limitations suggest that while the results are meaningful, they should be interpreted with caution, and further research is needed to confirm the generalizability and causality of the observed relationships.

Conclusion

The aim of this study was to identify key determinants of apartment rental rates on the Booking.com platform. As the short-term rental market continues to evolve, understanding the factors driving apartment rental rates on Booking.com helps address the research gap left by the dominance of data analyses focused on the Airbnb platform. This work provides new insights and conclusions based on data collected specifically from Booking.com. The analysis was conducted using data from Polish cities, obtained through a Web Scraping script with the Selenium library, which enabled the collection of information on offers available on Booking.com. By applying quantile regression, the effect of individual factors on apartment rental rates was estimated, and the research hypotheses were tested.

The first hypothesis was related to variables in the category of affiliate programs. It was expected that participation in the Preferred and Preferred Plus programs would be positively associated with apartment rental rates. The results of the quantile regression supported this hypothesis, revealing the significance of both variables. Notably, participation in the Preferred Plus program was found to have a stronger effect on rental rate than participation in the Preferred program, aligning with expectations, as the Preferred Plus program attracts more customers and allows for higher rental rates. The Wald test did not show significant differences between the tested quantiles, suggesting that the parameter estimates are stable across different rental rate levels. However, an analysis

of the estimates plotted across quantiles provides valuable information that may not be captured by the Wald test alone. These plots reveal subtle relationships that are more apparent when looking at a larger number of quantiles. Specifically, the Preferred program appears to be most beneficial for apartments with moderate rental rate, whereas the Preferred Plus program is more advantageous for higher-end apartments. These results suggest that participation in affiliate programs such as Preferred and Preferred Plus enables hosts to charge higher rental rates, benefiting both customer acquisition and revenue generation. However, it is important to note that these programs involve fees, which complicates the estimation of their overall cost-effectiveness. Therefore, hosts should carefully weigh the costs and benefits before committing to affiliate programs.

The hypothesis regarding the effect of language skills on apartment rental rates assumed that knowledge of foreign languages would positively influence apartment rental rates. The results of the analysis indicated partial rejection of this hypothesis due to ambiguous findings, particularly concerning Russian, which exhibited a negative relationship with apartment rental rates. This unexpected negative relationship warrants further investigation to understand the reasons behind this phenomenon. Conversely, a positive and significant relationship was observed for other languages such as English, German, and Ukrainian, supporting the hypothesis. These findings suggest that hosts who invest in learning foreign languages, especially German, could experience financial benefits by attracting a broader range of international guests.

The hypothesis concerning the relationship between specific apartment ratings and rental rates suggested that these ratings would have a significant impact on apartment rental rates. Based on the research, there is no reason to reject this hypothesis. The negative relationship between the evaluation of value for money and apartment rental rates may stem from higher customer expectations for more expensive apartments. Guests paying higher rental rates may have higher standards, resulting in lower ratings if their expectations are not fully met. On the other hand, the positive relationship between location ratings and apartment rental rates indicates that apartments with better-reviewed locations tend to have higher rental rates. The findings highlight the significance of location and value-for-money ratings in influencing apartment rental rates. These insights can help hosts understand which aspects of their offerings matter most to customers and how they can improve the overall guest experience.

The results of this study are valuable for a broad audience. Property owners can use this information to optimize their listings on the Booking.com platform, enhancing the competitiveness and profitability of their apartments. For researchers and analysts of the short-term rental market, these findings contribute to the growing literature on the sharing economy and the platform-based real estate market. Several avenues for further research exist. First, expanding the geographical scope of the study to include more countries would provide a global perspective on the determinants of apartment

rental rates. Second, spatial modeling could be employed to better account for local rental rate variations and spatial factors influencing property rental rates. Future studies could also explore the relationship between rental rate and collinear variables such as staff ratings, cleanliness, comfort, and amenities, which may provide deeper insights into their impact on property value.

There are some limitations to this work. Due to the large number of variables available on Booking.com, not all possible data could be collected, meaning that the analysis may have missed some important rental rate drivers. Additionally, the study focused only on the 25 largest cities in Poland, which limits the generalizability of the findings to the entire country. Despite these limitations, the study provides valuable conclusions and serves as a solid foundation for future research. In conclusion, this work fills an important research gap and offers new insights into the determinants of apartment rental rates on the Booking.com platform, contributing to a better understanding of the short-term rental market.

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Annex

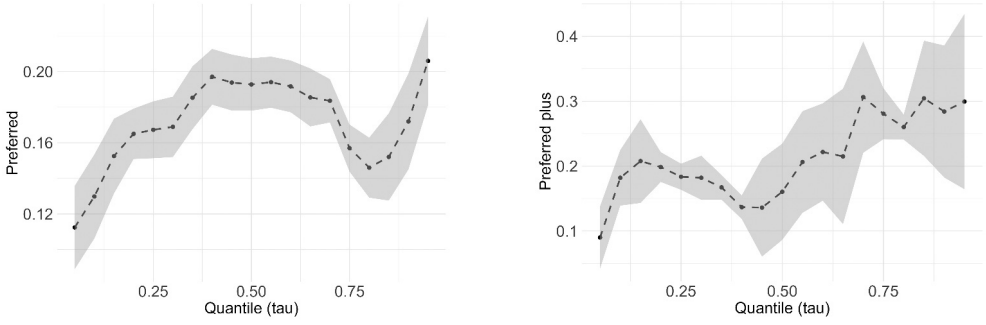
Table 1A. Descriptive statistics of variables

Variable	Min	25%	Median	Mean	75%	Max	SE
ln(Rental rate)	3.4	4.7	4.9	4.9	5.2	6.9	0.45
Preferred Program	44.8	120	157.5	180.5	211.2	1030.2	103
No Preferred Program	31.2	101.5	130.5	152.6	175	1030.2	99.8
Preferred Plus Program	68.7	115.5	154	197.8	234.8	777.5	132
No Preferred Plus Program	31.2	104.5	135	157.4	180.5	1030.2	100
TV available	31.2	105	135.5	158.8	182.5	1030.2	101
TV unavailable	36.7	98.5	131	149.5	172.7	1030.2	101
Wifi available	31.2	105	137.5	159. 9	183	1030.2	102
Wifi unavailable	34.7	99.8	129.5	150.1	171	1030.2	96.7
Kitchen available	31.2	105	139	161.2	183	1030.2	107
Kitchen unavailable	39.5	102.2	131.1	153.7	179.6	1030.2	92.1
Balcony available	36.7	108.6	143	165.3	190	1030.2	105
Balcony unavailable	31.2	100.7	130	151.4	172.5	1030.2	96.3
Air conditioning available	38.2	117.4	151.8	175.6	200	1030.2	104
Air conditioning unavailable	21.3	100.8	131.9	153	175	1030.2	99.4
Bathroom available	31.2	105	138.5	159.5	182	1030.2	100
Bathroom unavailable	34.7	99.5	127.3	152.6	179.5	1030.2	104
Host speaks English	31.2	105	136.5	159.5	182.5	1030.2	103
Host does not speak English	37.3	100	127	146.2	170.8	1008	77.3
Host speaks German	31.2	111.7	144.5	169.8	202.2	1030.2	98.7
Host does not speak German	31.7	103	134.5	155.7	178	1030.2	101
Host speaks Ukrainian	31.2	106.2	144.5	170.8	199.5	1030.2	116

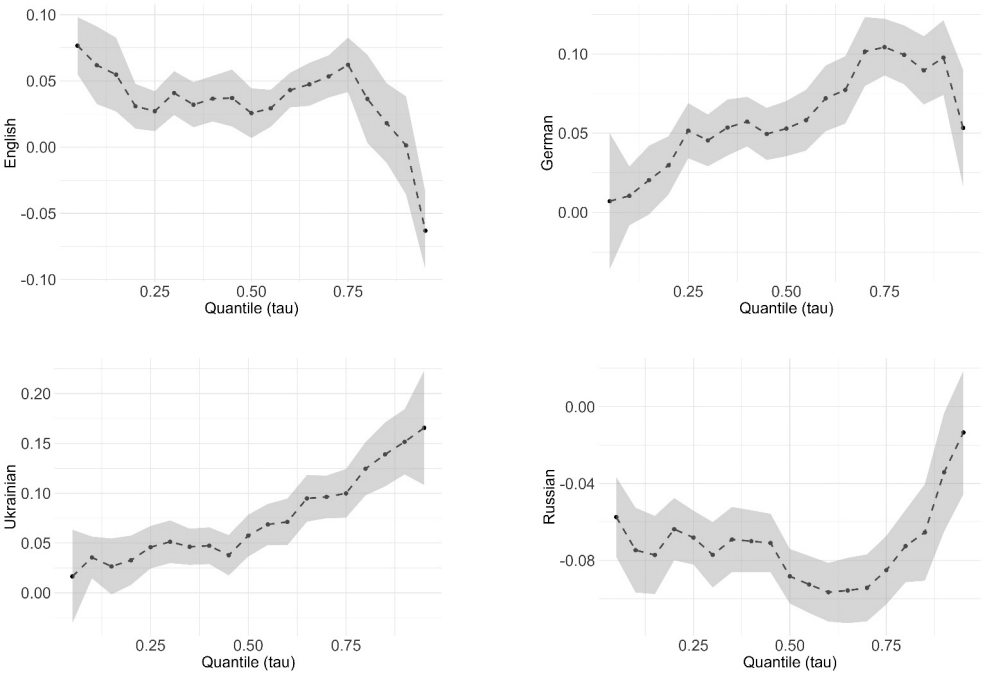
Host does not speak Ukrainian	31.7	104.5	135	156.2	180	1030.2	98.4
Host speaks Russian	31.2	100	135	156.4	180	1030.2	98.4
Host does not speak Russian	31.7	105	135.5	158.5	182	1030.2	102
Variable	Min	25%	Median	Mean	75%	Max	SE
Smoking is allowed	44	104	135	141	162	652	67.7
Smoking is not allowed	31.2	104.5	135	158.5	182	1030.2	102
Pets are allowed	31.2	102.5	134.5	153.6	179.5	1030.2	94
Pets are not allowed	31.7	105	137.5	161	182.5	1030.2	105
Masovian Macroregion	50	120	160.5	178.45	200.5	1032.2	109.1
Central Macroregion	31.7	96	124.5	133.3	157.5	690	58.3
Eastern Macroregion	41.5	90.4	119.5	128.3	149.1	399.5	53.9
North-Western Macroregion	40.3	111.3	140	165.2	191.5	1032.6	122.8
Northern Macroregion	34.7	98.5	122	150.6	166	1032.6	122.7
South-Western Macroregion	37.3	109.4	137.5	153.4	172.8	624.5	74.5
Southern Macroregion	31.3	107.5	144.5	164.2	193.5	1032.6	94.3
Distance from the center (m)	20	600	1200	2019	2400	17200	2190.1
Proximity to public transport (m)	30	550	950	1232	1400	12000	1337.9
Area	15	30	38	40.3	48	245	16.7
Value for money	2.5	8.4	9	8.82	9.4	10	0.85
Location rating	2.5	9	9.4	9.28	9.7	10	0.63
Number of reviews	1	19	57	210	152	11294	564.6

Source: own elaboration.

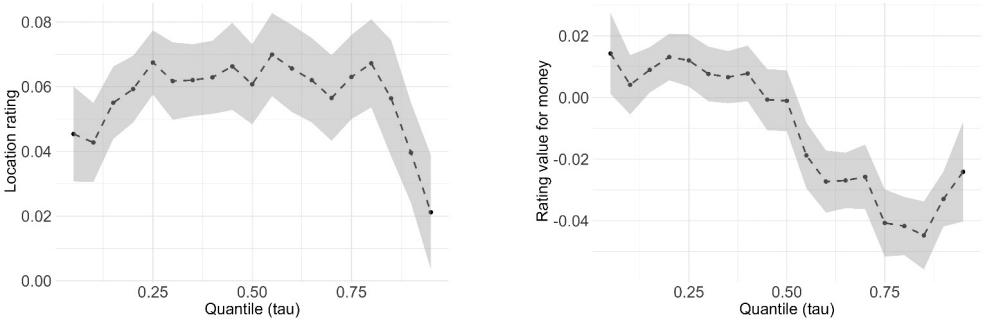
Figure 1A. Estimation of coefficients of variables from the affiliate programs category in individual quantiles of the rental rate distribution



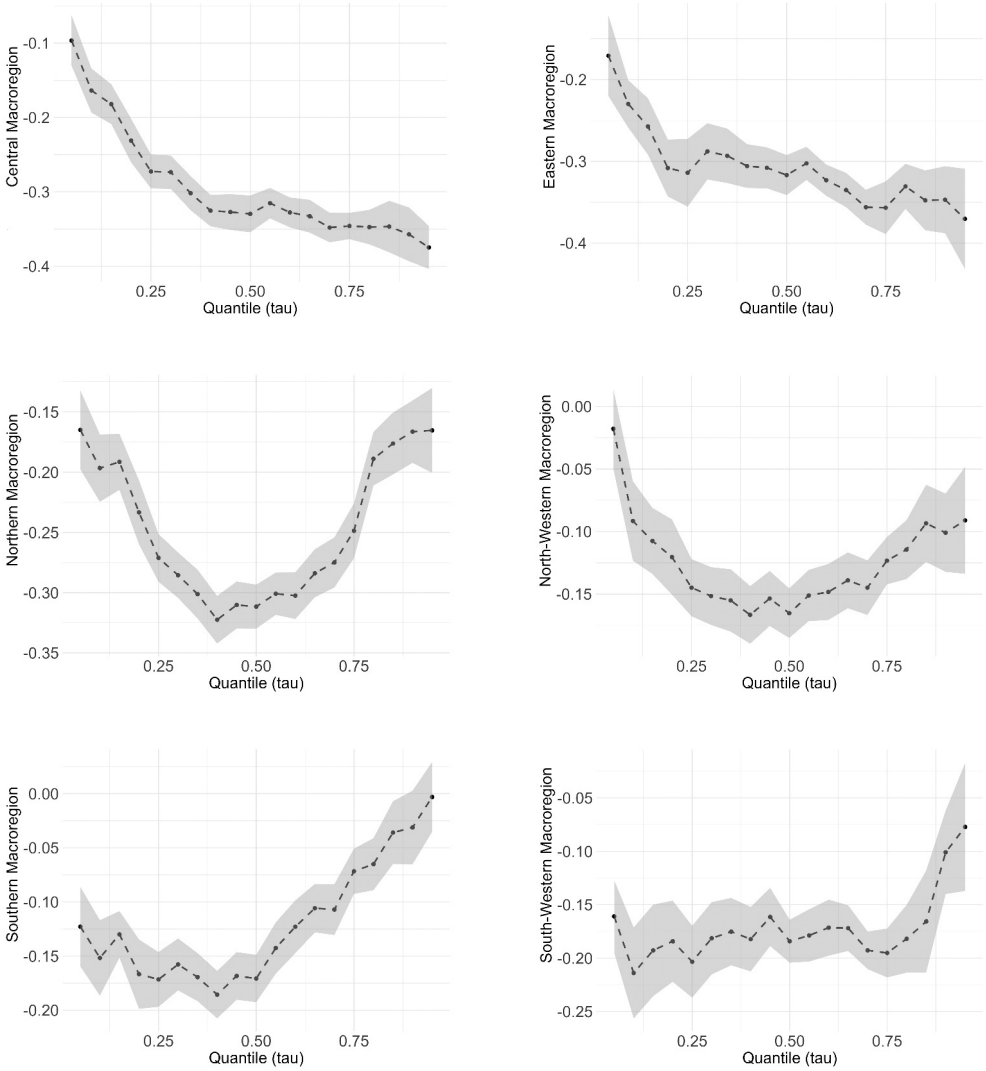
A. *Estimation of coefficients of variables from the language category in individual quantiles of the rental rate distribution*



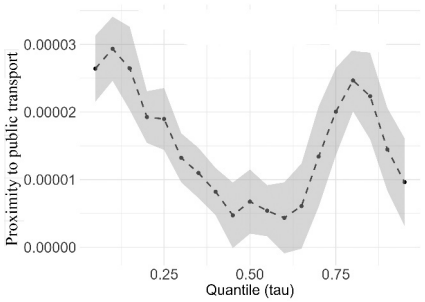
B. *Estimation of the coefficients of the variables from the rating category in the individual quantiles of the rental rate distribution*

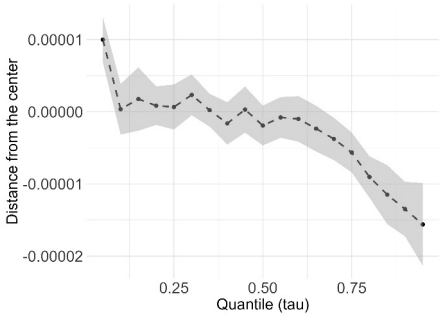


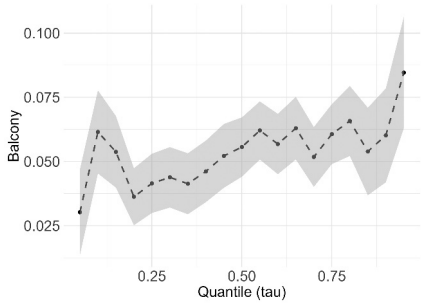
C. *Estimation of the coefficients of the variables from the NUTS1 regions in the individual quantiles of the rental rate distribution*

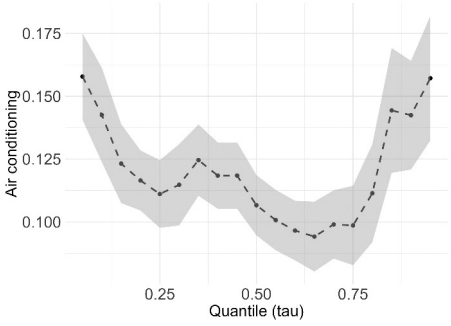


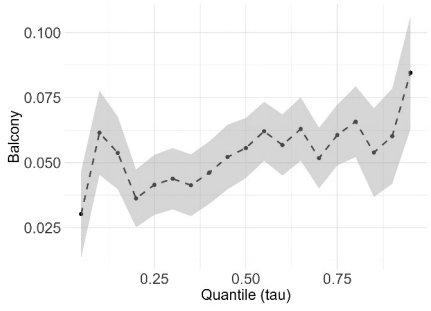
D. *Estimation of the coefficients of control variables in individual quantiles of the rental rate distribution*

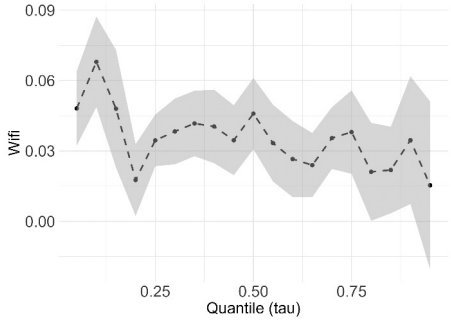


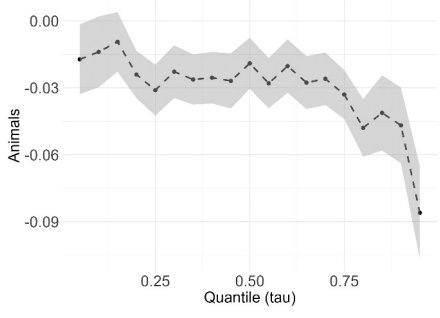


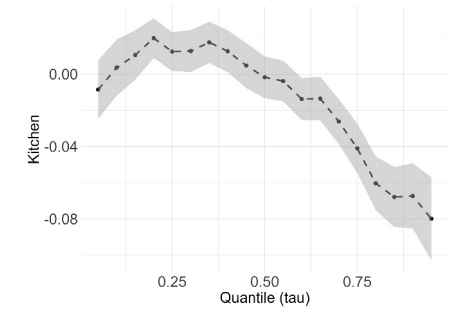


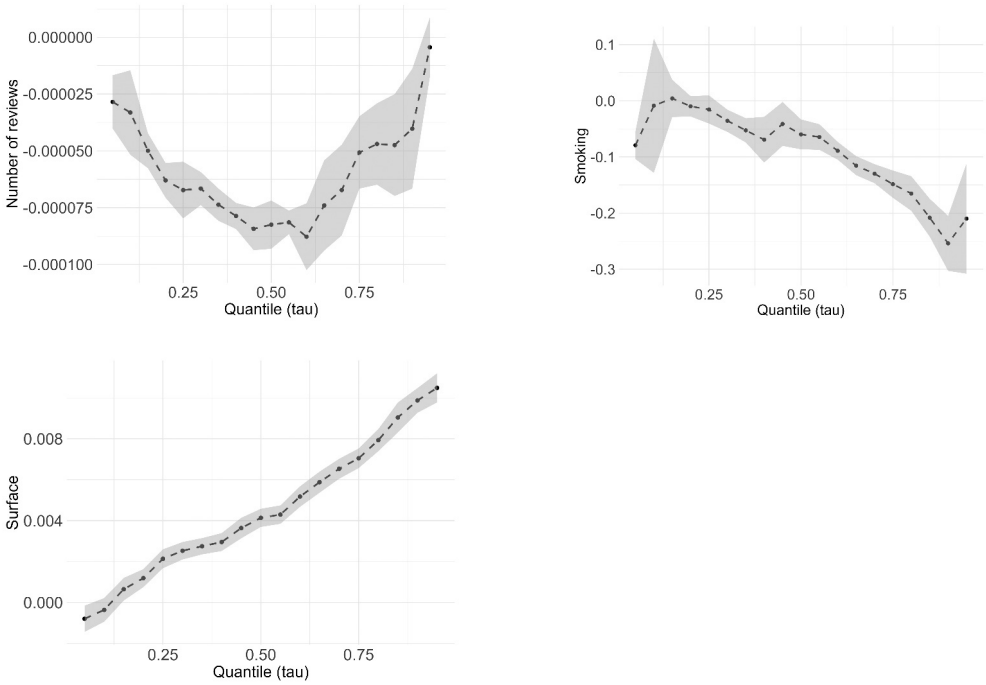












Note: The dashed black line denotes the quantile regression estimates for each quantile, with the 95% confidence interval in gray.

Source: own elaboration.