Understanding Airbnb Supply in Rome: Multivariate Analysis of Prices and Accommodation Patterns

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Abstract. The repercussions resulting from the succession of unregulated tourist activities, exemplified by overtourism, are also evident in the residential market, particularly within the short-term rental sector. These are commercial environments whose developmental rules and evolution over time frequently do not adhere to standards of normalcy and traceability of their characteristics across various spatial scales, from neighbourhood to city. This arises from the unpredictability of price creation processes at a regional level concerning (e.g.) the target demographic that requires short-term renting.

The phenomenon of short-term rentals in the city is investigated in this article, with the primary attention being placed on the qualities that are unique to this phenomenon in terms of demand, supply, and spatial considerations. Rome is utilized as the case study. The primary evidence across various analytical scales (urban area, municipality, city) is emphasized, examining their empirical relationships concerning the relevant territorial setting.

Keywords: Airbnb · short-term renting · multivariate analysis

1 Introduction

Mass tourism is a phenomenon that is progressively proliferating globally. In European, particularly in Italy, locales and cities (e.g., Rome, Florence and Venice), the repercussions of over tourism are manifest, associated with the influx of visitors to historical and cultural sites concentrated in relatively confined areas, often marked by severely limited spaces. The emergence and expansion of sharing economy platforms have significantly enhanced mass tourism by altering the accessibility/utilization of tourism resources and services. One viable alternative to long-term hotel stays is home-sharing, also known as short-term renting [1].

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Eurostat data on collaborative economy platforms indicates a substantial increase in short-term rentals in tourist cities from 2018 to 2023 [2]. This trend has been fueled in part by the rise of collaborative economy platforms that facilitate the free or paid sharing of goods and services between private individuals [3]. After a record-breaking 2019 with 512 million overnight stays, the number of annual guest nights in short-term accommodation booked through online platforms in the European Union (EU) contracted by 47% in 2020 (272 million) due to the COVID pandemic, according to EUROSTAT statistics on the "Collaborative economy platforms". However, 2023 saw a strong rebound, with over 719 million overnight stays. Italy (+27.5%) and Greece (+21.6%), in particular, are showing growth from 2022 year to 2023 that surpasses the overall growth of the EU. With about seven million overnight stays in 2023, Italy also topped the list of countries with the most international tourists. Based on these statistics, Rome ranked second among the four platforms for overnight stays in 2023 with 12.5 million, just behind Paris with 19.3 million. Barcelona, Lisbon, and Madrid followed with 10.9 million, 10.5 million, and 9.5 million, respectively. In all, out of all the overnight stays in the EU booked through the four platforms, which total 719 million, 8.7 percent, or 62.8 million, occurred in these five cities. Figure 1 shows the number of guest stays in the European Union from 2018 to 2023.

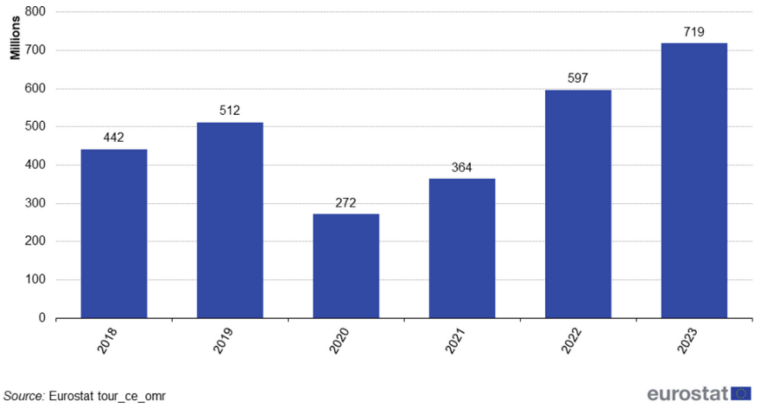

Fig. 1. Annual guest nights in the EU, 2018–2023. *Source*: [4].

As a result of the proliferation of collaborative economy platforms, a considerable number of homeowners have opted to rent out their residential units on a short-term basis using platforms. This is done with the intention of generating substantial profits in the shorter term, as opposed to relying on traditional long-term leases [5]. The potential for a more lucrative source of income motivated individuals to invest in real estate by acquiring new properties for the short-term rental market, often at prices exceeding their true value. The primary entities in this market consist of five global companies (Airbnb, Booking.com, Expedia/VRBO, Tripadvisor, and Tujia), who collectively represented over seventy-five percent of the sales in this global market in 2019 [6]. As of 2025, Airbnb is the preeminent platform for short-term rentals globally, featuring over eight million

active listings from more than five million hosts throughout over 240,000 countries and cities [7].

The purpose of this study is to analyse the supply, demand, and locational characteristics via Airbnb that are related with the short-term rental market in Rome. The paper is structured as follows: Sect. 2 provides a review of the sector literature on the impacts of Airbnb on the residential market (2.1) and a description of the proposed analysis methodology (2.2). Section 3 presents the results of the investigation and Sect. 4 the discussion.

2 Materials and Methods

2.1 How Airbnb is Influencing the Housing Market: Literature Survey

The absence of regulation in this economic sector has resulted in numerous (predominantly adverse) consequences in prominent tourist destinations, which have been thoroughly examined in scholarly literature. Zervas, Proserpio, and Byers (2017) demonstrated that Airbnb's entry into the Texas hotel business adversely affected it, revealing that a 1% increase in Airbnb listings led to a 0.05% decline in quarterly hotel revenues [8].

Several authors have indicated that the proliferation of short-term rentals has exacerbated tourist pressure, resulting in a diminished availability of affordable housing for residents and contributing to the gentrification of specific neighbourhoods, where residents are supplanted by tourists, thereby causing significant alterations and distortions in the residential property market for both purchasing and renting [9]. Other scholars have demonstrated that these effects are more pronounced in urban centres, where tourist attractions are prevalent, resulting in a heightened concentration of short-term rental accommodations and subsequently causing an unequal development of supply and demand [9]. The spread of collaborative economy platforms has brought about profound changes in the tourism accommodation sector. The academic literature on this topic has demonstrated the varying degrees of substitutability between the hotel market and short-term rentals, depending on the services offered, which differ significantly and target distinct customer segments. Yoong, K., Woltering, R.-O., and Heo, C.Y., in their study focusing on the cities of Barcelona, London, and Paris, explored the impact of home-sharing platforms such as Airbnb on the hotel industry. They found that the severity of the effect varies depending on the market, the hotel segment, and the type of Airbnb listing [10]. Yang and Mao, utilizing an extensive dataset encompassing 28 locations in the United States, demonstrated that a 1% rise in hotel room rates resulted in a 1397% increase in the availability of accommodations on Airbnb [11].

Another element that has been brought to light in the literature is the concentration of supply in the hands of "professional" hosts who provide management services for multiple flats at the same time. This has the potential to have substantial consequences on urban dynamics, overtourism, and the behavior of operators [6]. Several authors have focused on the importance, relationships, and influences between content created directly by hosts (Market-Generated Content – MGC) and that created by guests (User-Generated Content – UGC); these factors influence both consumer intentions and choices, as well as hosts' marketing strategies on platforms, consequently affecting the

prices and characteristics of properties listed in the short-term rental market [12–16]. To mitigate the impact of the unregulated proliferation of short-term rental accommodations in tourist locales, some countries (e.g., Italy) and cities (e.g., London, Paris, Barcelona) have implemented legislation. Scholars examining the ramifications of Airbnb's presence on local communities have investigated legal and tax implications, as well as the means and consequences of enacting home-sharing ordinances (HSOs) to control the short-term rental industry [17].

As stated by Morales et all., the impact of Airbnb listings on a city as a whole is concentrated in the municipalities closest to tourist attractions, so Airbnb listings can influence how housing prices behave. In these districts, Airbnb listings can be identified as a factor driving up long-term rental prices [18].

The examination of pricing and availability of short-term rental housing is especially pertinent given the transition in housing utilization, from a conventional real estate asset influenced by standard market variations to an investment asset assessed through alternative valuation metrics, including tourist influx, occupancy rates, or associated services. These features that introduce greater price volatility are framed within the development of financialization models as described by [19].

2.2 Methodology

Subsequent to that theoretical framework, this research aims to describe the tourist rental market in the city of Rome from the perspective of pricing in the supply displayed on the Airbnb platform, providing an overview of the current situation of Airbnb listings. Data was collected, preprocessed, and analyzed using descriptive statistical techniques, variance analysis, and machine learning classification models. Several software tools were employed, including Excel, SPSS, and QGIS, to comprehensively describe the phenomenon under study.

The classification tree technique is a supervised machine learning method that seeks to partition the feature space into a smaller number of subspaces using a series of decision rules, ensuring that the response variable values are similar within each subspace. Used for both classification and regression tasks. It builds binary trees that recursively partition the dataset into increasingly homogeneous groups, using criteria such as Gini impurity for classification or mean squared error for regression. The tree grows in a greedy fashion and may be pruned afterward to prevent overfitting. The classification tree technique is highly valued for its interpretability, flexibility, and robustness. It can capture nonlinear relationships and variable interactions without prior assumptions and handles both numerical and categorical data, while being resistant to outliers and missing values. These features make CART particularly useful when the goal is to describe and understand patterns in data in a clear and structured way. In this study, the CART algorithm was applied, which is used for both classification and regression tasks. Cross-validation strategies and model selection techniques were implemented to maximize performance while maintaining interpretability, thereby preventing overfitting.

Dataset. This study utilizes publicly accessible secondary data from Inside Airbnb, which includes records of 12 characteristics of the tourist rental market in the city of Rome. The dataset comprises 125,390 records, divided into four time periods spanning

from the last quarter of 2023 to the third quarter of 2024. To ensure data quality and reliability, a cleaning process was conducted to remove corrupted, anomalous, missing, or duplicate records. Missing values were not imputed; instead, irrelevant data were eliminated and missing or outlier values were systematically addressed. The integration of different datasets resulted in a consolidated table covering the final quarter of 2023 and three quarters of 2024. We have used data from the last year openly available on the Inside Airbnb website, which is sufficient for the purposes of the exploratory study being analyzed in this research.

Variables. The dataset provides information on various aspects of the Airbnb short-term rental market in Rome, including different types of hosts, rental prices, host characteristics, minimum nights, number of reviews, availability, room type, and geolocation data to identify neighborhoods and urban zones of the city, among other attributes. For the analysis, rental price was used as the dependent variable, while the remaining characteristics served as predictors. It is important to note that there is no information available on the capacity of the accommodation, nor the start date of the offer on the accommodation platform.

3 Results

The analyses applied to the data set were firstly a study of EDA (descriptive analysis) and the testing of the hypotheses of normality (the variables do not present normality), homoscedasticity, independence, among others, with the objective of verifying whether the data set requires substantial transformations in some of its variables.

It can be observed that the price variable presents a percentage of missing or missing data, which reduces the data set of this variable to 112,000 observations. A collinearity and multicollinearity analysis of the variables that report on reviews (number_of_reviews, number_of_reviews_ltm, last_review, reviews_per_month) was carried out, with the result that all four variables show collinearity, which could undermine the model's stability and reliability. Therefore, following methodological criteria, three of the variables were excluded, retaining only the one that demonstrated the highest theoretical relevance and best statistical performance according to the Variance Inflation Factor (VIF) and significance tests. This decision helped reduce informational redundancy, enhance coefficient interpretability, and prevent distortions in the parameter estimates. For research purposes we have worked only with the variable number of reviews ltm, to avoid redundancy of information. In general, the frequency tables corresponding to the categorical variables Room_type and neighbourhoods and urban zones are as follows:

The Table 1 shows the existence of high price variations depending on the location and type of accommodation. It can be seen that the rental offer on Airbnb is highly concentrated in Entire Home typologies 76.2% followed by Private Room 22.5%, with hotel room or shared room alternatives representing 1.3% of the offer in Rome. At the neighborhood level, the supply is concentrated in the historic center of Rome, accounting for over 50% of the total supply among all housing alternatives.

The progressive increase in prices is significant for the period analyzed, with an average growth of 24% across the entire city, driven by a 36% increase in the historic

Table 1. List of Airbnb accommodation offerings for the third quarter of 2024, segmented by neighborhood as well as by type of establishment (Entire home/apt, Hotel room, Private room, Shared room).

Municipality	Entire home/apt		Hotel room		Private room		Shared room	
	Av.Price	%	Av.Price	%	Av.Price	%	Av.Price	%
I Centro Storico	**280**	**51.%**	**220**	**71.2%**	**194**	**49.0%**	**87**	**38.7%**
II Parioli/Nomentano	176	6.8%	106	3.2%	114	7.3%	58	5.0%
III Monte Sacro	212	1.7%	113	1.4%	84	1.9%	32	1.7%
IV Tiburtina	195	1.5%			79	2.7%	37	1.7%
V Prenestino/Centocelle	102	4.6%			74	5.1%	50	22.7%
VI Roma delle Torri	164	0.8%			77	1.2%	31	4.2%
VII San Giovanni/Cine.	207	7.7%	137	8.8%	106	9.3%	26	5.0%
VIII Appia Antica	162	2.5%	175	2.1%	110	3.3%	38	2.5%
IX Eur	215	1.3%	90	0.4%	94	1.0%		
X Ostia/Acilia	216	3.3%			97	2.0%	96	5.0%
XI Arvalia/Portuense	152	2.0%	152	0.4%	102	2.3%	37	6.7%
XII Monte Verde	183	5.6%	109	3.2%	126	4.8%	34	2.5%
XIII Aurelia	205	6.7%	172	8.1%	154	6.4%	27	0.8%
XIV Monte Mario	213	2.3%	117	1.1%	94	2.1%		
XV Cassia/Flaminia	170	1.8%	145	0.4%	97	1.5%	231	3.4%
Total	**233**	**22,927**	**198**	**285**	**150**	**6755**	**69**	**119**

The average rental price per night is indicated, as well as the percentage share of the supply by the neighborhood in relation to the total supply in Rome for each type of accommodation. *Source*: Own elaboration.

center. Only two districts show higher growth rates: 48% in Municipality VI (Roma delle Torri) and 46% in Municipality XIV (Monte Mario), both of which have a very limited supply. In fact, Municipality VI has the lowest number of listings in the entire city, with 279 properties in the third quarter of 2024. Additionally, it is worth noting that the average growth is influenced by the listing of atypical properties in these districts, featuring very high prices exceeding €1000 per night - a pattern that differs from the general trend observed in overall price growth.

Figure 2 illustrates the weight and spatial distribution of each type of property listed on Airbnb for the third quarter of 2024. These data align with those presented in Table 1 and highlight the significant predominance of entire home listings compared to other accommodation types on the platform. Section A shows a wide distribution of this type across the city center of Rome, with a share exceeding 50%. Outside the city center, listings are concentrated in neighborhoods bordering the *Vatican* area to the west and the *Termini* railway station to the east. Section B, which refers to hotel and aparthotel offerings, reveals their limited presence in the overall supply, along with their higher concentration within the historical center. Given the nature of these establishments, this category encompasses a broad range — from units with private bathrooms to guesthouses

or boutique hotel concepts — generally lacking traditional hotel services such as on-site dining. Section C of Fig. 2 shows the distribution of private rooms (with or without private bathrooms), a category again concentrated in the historical center, with notable presence around *Termini* and the *Vatican* areas. Finally, Section D displays the distribution of shared rooms, which are mainly concentrated around the *Termini* railway station.

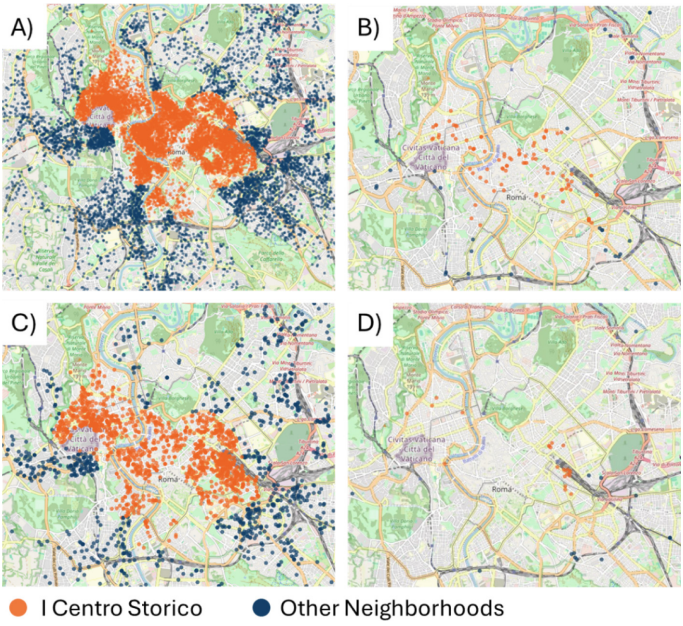

Fig. 2. Map of Rome showing the spatial distribution of Airbnb listings by room type. Fig. A presents the supply of Entire home/apartment, B shows hotel rooms, C refers to private rooms, and finally, and D illustrates shared rooms

The descriptive statistics for the quantitative variables are presented in the following table.

To verify if the data presents significant differences in terms of price in the 4 quarters under analysis, an analysis of variance (One-Way ANOVA) was applied, resulting in a (p-value) of less than 0.05, which indicates that there are significant differences in the price variable between the 4 quarters. The test carried out indicates that in the quarters 2023-Q4 and 2024-Q1 the prices vary between them and in comparison, with the other three quarters, the quarters 2024-Q2 and 2024-Q3 do not present a variation between them in terms of prices, but they do vary from the quarters 2023-Q4 and 2024-Q3. The results are shown in Table 2.

On demonstrating that there are price differences between the quarters of the year through the analysis of variance (ANOVA) and the graph of price differences by quarter. We proceed to carry out the supervised classification analysis by quarters, in order to be able to detect what differentiates each time of the year in terms of prices.

Table 2. Average price differences by quarters.

Quarter	N° cases	Mean	Deviation	Min-Max
2023-Q4	27,376	172,37	712,362	8–80.000
2024-Q1	26,543	187,00	625,570	10–80.000
2024-Q2	28,510	207,82	522,857	10–64.000
2024-Q3	30,086	213,37	653,220	8–72.000

Classification trees were constructed using the CRT (Classification and Regression Trees) method with "price" as the dependent variable. Machine learning technique is applied for each quarter. The Table 3 below shows a summary of the results obtained.

Table 3. Summary of CTRs.

	2023 Q4	2024 Q1	2024 Q2	2024 Q3
Average price	172,37	187	207,82	213,37
First segmentation variable	Mínimum nights	neighbourhood	neighbourhood	neighbourhood
Relevant variables	Number of reviews ltm, availability 365, room type	Number of reviews ltm, availability 365, room type.	Number of reviews ltm, room type, availability 365	Number of reviews, availability 365, room type
Higher average price	2360,39 Nodo 2	908,39 Nodo 8	1235,55 Nodo 8	880,87 Nodo 8
Minimum average price	95,12 Nodo 8	83,9 Nodo 14	78,90 Nodo 14	89,58 Nodo 14
Points of division	Minimun nights <= 362, >362, Number of reviews ltm, <= 0.5, > 0.5, availability 365, <= 365, > 365, room type	Neighbourhood Number of reviews ltm, <= 0.5, > 0.5, availability 365, <= 365, > 365, room type	Neighbourhood Number of reviews ltm, <= 0.5, > 0.5, room type, availability 365, <= 365, > 365	Neighbourhood Number of reviews, <= 0.5, > 0.5, availability 365, <= 365, > 365, room type
Singularity	23 cases with very high price in Node 2	few cases, high prices in Node 8	56 cases with very high price in Node 8	88 cases high prices in Node 8

- Tree 2023Q4 is unique in that it starts by dividing by minimum_nights, it identifies a clear difference between short and long term rentals with properties with stays over 362 nights, in this Q4 2023 analysis the number_of_reviews_ltm is very relevant.

- Tree 2024Q1 the first segmentation variable is neighborhood and shows the concentration of accommodation in the neighborhood I. The outliers are less extreme than in other trees; it is the most balanced and has a shallower depth.
- Tree 2024Q2 the first segmentation variable is neighborhood and clearly shows how more reviews lower the price, shows better differentiation by room_type. Outlier (Node 8) is very clear and bounded, the most structured and clear, and behaves more predictably and logically.
- Tree 2024Q3 is again segmented with neighborhood as the first variable, it is highlighted that few reviews raise the price. availability_365 generates strong outliers.

In the segmentations made in the classification trees for the different quarters, it can be seen the need to further detail the analysis by urban areas, due to the fact that the municipality with the highest presence of accommodation is the *Centro Storico* of Rome, which gives rise to the question of whether Municipality I presents significant differences by urban areas in terms of accommodation prices and the concentration of accommodation.

When the analysis was carried out using the classification tree technique, an adjustment was made to the territorial segmentation of the lodgings, moving from a division by municipality to a classification based on specific urban zones within each municipality. The results obtained indicate that the urbanistic zone variable is not a determining factor in the variation of lodging prices. This conclusion is supported by the data presented in Table 4.

Table 4. Importance of independent variable of CTRs.

Independent variable	Normalized importance [%]
Availability_365	100,0
Number_of_reviews_ltm	38,1
Minimum_nights	34,7
Room_type	29,3
Z_URB	0,1

Although the results obtained indicate that the urbanistic zone variable is not a determining factor in the variation of lodging prices, it is important to consider these findings in a relative manner. The analysis carried out was of a general nature, so it cannot be ruled out that, when examining the distribution of urban areas within each municipality individually, different results may be obtained in which this variable have a significant impact. In this sense, future research will study each municipality in more detail, allowing for a more detailed evaluation of the influence of urban zones on the determination of lodging prices. This first analysis is therefore a starting point for more specific studies.

Prices in the *Centro Storico* neighborhood are significantly higher than in all other neighborhoods, as shown in Fig. 3. This difference, both in average price and in the availability of property listings, is reflected in the fact that *Centro Storico* is the only

neighborhood above the average, while the other fourteen neighborhoods remain below that level in the third quarter of 2024. These price differences are evident across all types of available accommodations, both in terms of averages and data dispersion, with a high number of outliers observed particularly in the cases of "entire home/apartment" and "private room" listings.

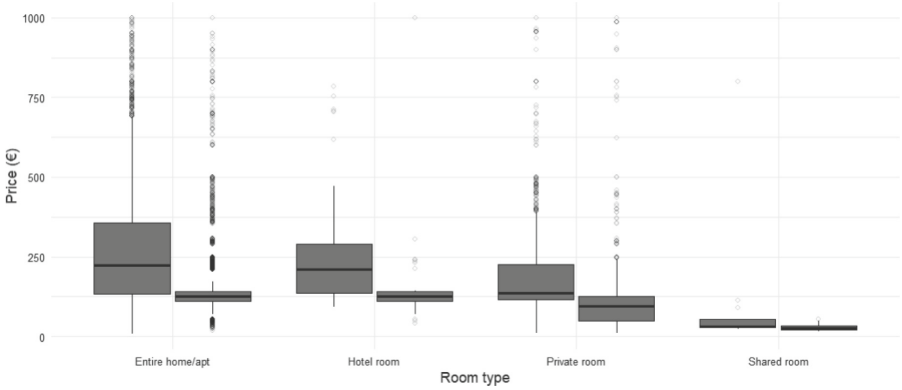

Fig. 3. Boxplot diagram showing the price distribution for each type of listing, with the city center of Rome segmented on the left and the remaining neighborhoods on the right.

The next notable aspect concerns reviews associated with listings. Table 5 shows the average price as the number of reviews increases, considering values of 0 (no reviews), 1, 2, 10, and the case labeled 100*, which represents the average for listings with 90 to 109 reviews, due to the lower number of individual data points available to calculate a reliable mean. A general decrease in prices is observed as the number of reviews increases, with the lowest average prices corresponding to the highest number of available reviews. For "entire home/apartment" listings, average prices decrease by between 45% and 57% when comparing listings with no reviews to those with around 100 reviews. These reductions are even greater for "private room" listings, ranging from 51% to 65%. A similar trend is observed for "hotel room" and "shared room" types, with proportionally larger reductions when the initial prices are lower. This pattern is exemplified in the third quarter of 2024, during which the price differences between listings with 0 reviews and those with approximately 100 reviews show a decrease of 50% for "entire home/apartment," 57% for "hotel room," 51% for "private room," and 77% for "shared room". In the analysis, segmentation by room type is necessary due to the different configurations of the supply. The use of aggregated data leads to an increased weight of lower-priced offerings, such as shared-use rooms, resulting in average data showing a larger decrease than what is actually observed for each room type.

Finally, the analysis of property concentration yields representative results for the city of Rome, both in terms of specific points in time for each quarter and in the temporal evolution of the data. From a point-in-time perspective, there is a notable level of concentration in the supply, where the 33,833 listings are distributed among 18,445 user accounts, resulting in an average of 1.83 listings per account. The user with the highest

Table 5. Evolution of rental prices according to the number of reviews over the past year on the Airbnb platform. *Source*: Own elaboration.

		Number of Reviews				
		0	1	2	10	100*
Entire Home/Apartment	2023 Q4	261	236	194	179	112
	2024 Q1	275	214	200	186	135
	2024 Q2	299	259	223	190	163
	2024 Q3	338	241	224	215	170
Hotel Room	2023 Q4	268	165	149	89	
	2024 Q1	213	178	135	114	
	2024 Q2	244	194	176	119	
	2024 Q3	246	239	240	107	
Private room	2023 Q4	203	132	113	82	71
	2024 Q1	192	127	117	110	77
	2024 Q2	200	155	144	95	91
	2024 Q3	197	146	147	124	97
Shared Room	2023 Q4	125	42	40	29	
	2024 Q1	75	35	85	43	
	2024 Q2	106	53	49	30	
	2024 Q3	112	43	64	26	

number of properties — 302 in the third quarter of 2024 — accounts for 0.89% of the total Airbnb supply in Rome for that quarter. The top 10 users by number of properties, with a combined total of 1032, represent 3.05%, while the top 100 users control 3455 listings, accounting for 10.21%. From a temporal perspective, there has been an increase in concentration over the last four quarters. For example, the share of listings held by the top 10 accounts increased from 2.86% to 3.05%, while the share held by the top 100 accounts rose from 9.46% to 10.21%, indicating a trend toward greater concentration. In this regard, not only is there a continued growth of accounts managing multiple properties throughout the period, but also the emergence of new accounts that, within two to three quarters, go from managing zero properties to managing between 10 and 32.

Figure 4 shows the existence of accounts with a large number of housing units, which, however, are widely distributed without a noticeable high concentration in specific areas. The historical center of Rome — delimited by the Vatican to the west, *Termini* railway station to the east, *Villa Borghese* to the north, and the neighborhoods of *Trastevere* and *Testaccio* to the south — concentrates the supply of these hosts.

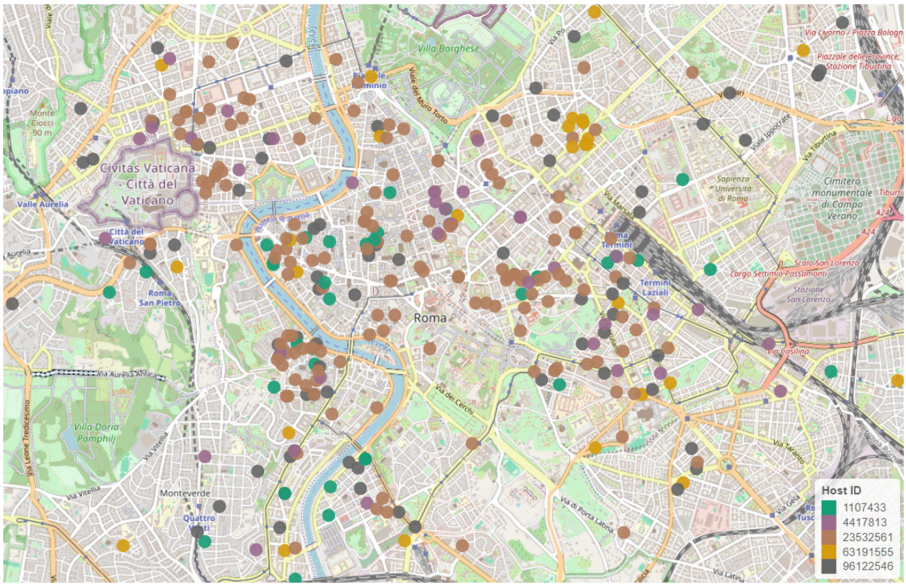

Fig. 4. Spatial representation of the dwellings managed by the five most representative host_id accounts.

4 Discussion and Conclusions

The study's primary objective of elucidating the key spatial-logistic attributes of the short-term rental market in Rome is corroborated by results that align with existing literature, encompassing aspects such as supply, room type, year-round availability, minimum stay requirements, user ratings, and property concentration. This analysis indicates a substantial majority of housing supply in the city's historic centre, where prices are markedly elevated compared to other neighbourhoods. The price of accommodation is directly correlated with the property's availability and inversely correlated with the number of reviews. However, no relationship has been observed between accommodation prices and the number of properties owned by a given *host_id*.

The minimum number of nights booked influences the prices in the last quarter of the year it can be observed that only 0.1% of the accommodations represent long term rentals, accommodations with fewer reviews have an higher average price. Properties with full availability during the year and which are complete flats tend to have higher prices.

For the first quarter of the year, the municipality where the accommodation is located starts to be decisive, Municipality I concentrates the highest prices of the accommodation offered with average prices of 224.76, with Municipality X joining this municipality. Likewise, accommodation in the in the historic center with less than 0.5 in number of reviews in the last year has prices of 345.55 higher than the average of the Municipalities I, X. High availability (365 days) correlates with higher prices, accommodation with fewer reviews has a higher average price. Properties with full availability throughout the year and which are complete flats tend to have higher prices.

The accommodations with the lowest average prices in Municipality I and X, are those with reviews above 0.5 and the whole flats stand out with a higher average price than the other room types.

In the second quarter, the Municipality I *Centro Storico* of the city of Rome concentrates the highest prices of the accommodations offered with average prices of 260. Likewise, the accommodations in the historic center with less than 0.5 in number of reviews in the last year have prices of 377 higher than the average of Municipality I. The minimum number of nights influences prices in the last quarter of the year, with accommodation with fewer reviews having a higher average price. Properties with full availability in the year and which are full flats tend to have higher prices.

The accommodations with the lowest average prices in Municipality I are those with reviews above 0.5 and the whole flats stand out with a higher average price than the other types of room type. Node 2, which concentrates accommodation outside the *Centro Storico*, shows that accommodation with 1.5 or more reviews in the last year has lower prices than those with fewer reviews in the last year. It can also be observed that the type of accommodation influences the average price, being higher for whole flats than for other types of accommodation, so that the availability and type of accommodation make the difference in the deep branches.

In the quarter 2024Q3, the Municipality I corresponding to the *Centro Storico* entre of the city of Rome concentrates the highest prices of the accommodations offered with average prices of 260. Also, the accommodations of the *Centro Storico* with less than 0.5 in number of reviews in the last year have prices of 377 higher than the average of the Municipality I.

The results open up future lines of research with potential impact both temporally and spatially. Extending the temporal horizon of the analysis would allow for the observation of long-term trends in this type of housing supply and could also enable comparisons in relation to regulatory changes affecting the sector. On the spatial side, further developing the analysis at the level of urban zones may provide greater depth to the study [20–23]. Another promising line of inquiry lies in comparing the results obtained for Rome with those of other cities, at the Italian, European, and international levels.

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Attribution of the parts of the text is the result of the joint work of all authors and will be attributed equally.

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