International Journal for Research in Tourism and Hospitality
Published by: **Green Publication Services**
Volume 01 Issue 02 June 2026

ASSESSING AIRBNB LISTING CHARACTERISTICS AND PRICING PATTERNS IN THE SHORT-TERM RENTAL MARKET

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ABSTRACT

Airbnb has become a major component of the urban short-term rental market, yet listing prices vary considerably according to accommodation type, location, and host-related characteristics. We analyzed 48,884 observations of Airbnb listings that excluded zero-priced observations. Using descriptive statistics, comparative tests, Spearman correlation, spatial analysis and multiple regression, the effects of room type, borough, minimum night requirements, review activity, host listing concentration, and annual availability on nightly prices were evaluated. It was found that there was a significant difference in the prices for various categories of accommodation and geographic regions. The private and shared rooms were significantly less expensive than an entire room or apartment, and Manhattan had the highest median nightly rate of the five boroughs. The minimum nights, the number of reviews, the number of hosts and the availability were weakly associated with Price. The regression model accounted for around 47.3% of the variance in the log-transformed prices, with room type and borough being the most important factors. Whole rooms or apartments were found to be much more costly than a private room, while shared rooms were found to be less costly. There was also a premium in the Manhattan listings over similar listings in Brooklyn. In sum, the study shows that the main factors that influence Airbnb prices are accommodation type and spatial location, whereas the impact of the review and operational characteristics is comparatively minor.

Article History:

Article Type: **Review**

Received Date: **10/05/2026**
Revised Date: **11/06/2026**
Accepted Date: **19/06/2026**
Published Date: **26/06/2026**

Keywords: Airbnb; short-term rentals; listing characteristics; pricing patterns; room type; spatial analysis

1. Introduction

Airbnb has significantly disrupted the accommodation industry by allowing individuals to rent their homes, rooms, and shared spaces online. It started as a peer-to-peer alternative to traditional hotels and has grown into a big and geographically widespread market of short-term rentals. Its expansion in many countries shows that digital intermediation has transformed the tourism supply, opened new accommodation options and developed new income streams for hosts (Adamiak, 2022). Besides monetary returns, social interaction, underutilised property use flexibility, and a perceived benefit of consumption in sharing are drivers of participation (Bremser & Wüst, 2021). Meanwhile, the growth and commercialisation of Airbnb have raised concerns about pricing practices, market concentration, housing scarcity and the transformation of urban neighbourhoods.

Hosts have a diverse market segment, causing Airbnb prices to greatly differ between listings. Nightly rates are subject to room type, neighbourhood, accessibility, local demand, review activity, minimum stay, host experience and annual availability. Airbnb prices are determined by individual or professional hosts, whose goals, information and strategies vary from those used in standardised hotel pricing. The emergence of the professional operators and multi-listing hosts has also changed the platform's structure by adding more systematic revenue management and portfolio-based pricing practices (Cocola-Gant et al., 2021). Research additionally suggests that skilled players hold the potential to affect game dynamics, provide conditions, and govern platforms, which highlights the importance of separating casual hosts from professionally organised operators (Chen et al., 2023). The developments mentioned above underscore the importance of listing level analysis to comprehend the pricing process in the short-term rental market.

Airbnb listings can have broader urban impacts and housing-market impacts because there are more listings in a particular geographic area. Growth in short-term rentals could lead to a reduction in the long-term tenancy of residential properties, influence local rents and property values, and put pressure on neighbourhoods that are popular with tourists (Benítez-Aurioles & Tussyadiah, 2020). Another study in Portugal also indicates that Airbnb rental activity can impact the rents and property prices of housing units, but this impact varies between different neighborhoods and housing types (Franco & Santos, 2021). Other evidence indicates that short-term rental platforms can have an impact on house prices and market liquidity, especially if tourism demand and platform activity are spatially clustered (Gárate Alvarez & Pennington-

Cross, 2023). The impacts are thus not likely to be consistent both between and within cities, as recent studies have documented differential impacts (Congiu et al., 2025).

Overtourism, neighbourhood change and gentrification are closely linked with these spatial effects. Online short-term rental services could exacerbate the tourist pressure in highly populated metropolitan areas and drive commercialization of residential areas (Celata & Romano, 2022). A further line of evidence from the spatiotemporal patterns suggests that the effect of Airbnb activity on rent levels, housing prices, and gentrification patterns is potentially complex (Lee & Kim, 2023). Multi-listing is especially relevant because hosts who own multiple properties can cut down on the supply of long-term rental properties and can also drive up the price of rents (Morales-Alonso & Núñez, 2022). These concerns have led to the adoption of registration systems, ceilings on the number of listings, taxation, zoning, and restrictions on professional hosting.

Yet, regulation must strive to balance tourism benefits, host income opportunity, consumer choice and housing protection. Platform rules and public regulation can affect the availability of listing, participation in the platform, and pricing, but their impact depends on how they are enforced, the local market conditions, and the behaviour of the hosts (Chen et al., 2021). Short-term rentals can also be revealed to be weak to market shocks. COVID-19 has impacted travel demand and tested Airbnb's business model, and the accommodation markets enabled by platforms are sensitive to external crises and quick shifts in tourism behaviour (Dolnicar & Zare, 2020).

Although there has been a vast amount of research conducted on the impacts of Airbnb on urban areas, there remains a need for empirical research which links Airbnb listing details with observable pricing trends. Such analysis can help to decide if the difference in prices is mainly due to the room category, location or if review activity, host concentration, minimum stay policy and availability have a significant part to play in price differences. Improving the understanding of these relationships can inform host decisions on pricing, traveller understanding of the market, and aid policymakers to differentiate normal home-shares from commercially driven short-term rental activity. This is particularly important in concentrated urban markets where there may be significant price variation in accommodation between different neighbourhoods or sections of neighbourhood within the same city.

Objectives

1. To explain the main features and value of Airbnb places in the market for short-term rentals.
2. To determine whether there are significant spatial pricing differences, and to compare the prices of rooms for a given geographic area and room type.
3. To identify the independent listing features to be associated with nightly price through comparative, correlational and multivariable analysis.

2. Methodology

2.1 Research Design

The current study was of a quantitative, cross-sectional and secondary data research type to investigate the characteristics of the Airbnb listings and prices in the short-term rentals market of New York City. This approach was chosen because of the availability of the dataset with listing-level information that is collected at a given time.

2.2 Data Source

The data analyzed is part of the New York City Airbnb Open Data for the year 2019. The database includes 48,895 Airbnb listings and 16 variables that include listing information, host information, borough, neighbourhood, geographic coordinates, room type, price, minimum night stay, review activity, host listing concentration, and annual availability. Data are for Airbnb listings in Manhattan, Brooklyn, Queens, Bronx, and Staten Island (Dgomonov, 2019).

2.3 Study Population and Unit of Analysis

The study population were Airbnb properties that were listed throughout NYC between October 2016 and December 2019. Individual Airbnb listings were analysed individually. Data for all five boroughs and 221 neighbourhoods were included. The main types of rooms in the principal room were complete apartment, private room, and shared room. Only records were kept when they were unique listing identifiers and provided valid information for primary analytical variables.

2.4 Study Variables

The dependent variable was the price that Airbnb advertised for a night's stay in USD. Independent variables were room type, borough, neighbourhood, latitude, longitude, minimum nights, the number of reviews, reviews per month, the number of host listings calculated, and availability over 365 days. Record identification (listing ID and host ID) was used for record identification but not included in the inferential analysis as it was not an analytical characteristic; listing and host names did not have an analytical characteristic and were not included in the inferential analysis. In addition, a review status variable was added to differentiate listings that have reviews from those that do not have reviews.

2.5 Data Cleaning and Preparation

Duplicate records, missing data, non-consistent coding, and implausible observations were checked in the data. Checking of listing IDs was done to ensure uniqueness and categorical variables were checked to ensure consistent spelling and grouping/definition. Where necessary, the price was converted to a numeric format. Price listings that were not valid for the main price analysis were those that showed no nightly prices.

2.6 Price Distribution and Outlier Treatment

Histograms, boxplots, percentiles, skewness and the interquartile range were used to assess the distribution of price. The price values were strongly right-skewed, so both raw values and natural log-transformed values were taken into account in Airbnb. There were no automatic removals for extreme prices, as some may be a genuine premium or luxury listing. Rather, analyses were carried out with the whole set of data and after excluding invalid and very extreme data, to see if the primary results were consistent.

2.7 Descriptive Statistical Analysis

Categorical data, e.g. borough, room type, were coded, and frequencies and percentages were calculated. The mean, median, standard deviation, interquartile range, minimum and maximum values were used to summarize continuous variables such as price, minimum nights, number of reviews, reviews per month, host listing count, and availability. As the median price is not as influenced by extreme values and is a better measure of a typical listing price, this was emphasised.

2.8 Comparative and Correlation Analysis

Airbnb prices were benchmarked on a room type, borough and neighbourhood group basis. When the assumption of normality and equal variance were reasonably met, one-way analysis of variance was used. In the case of a strongly non-normal distribution, the Kruskal–Wallis test was applied. To determine significant differences, post-hoc tests were performed. Pearson correlation was used for nearly normal variables and Spearman's rank order correlation for non-normal variables to check the relationship of price with continuous listing characteristics of the data.

2.9 Regression and Spatial Analysis

Multiple regression analysis was performed to determine the listing features that are independently associated with Airbnb price. The main outcome variables used were the natural logarithms of prices to minimise skewness. The following factors were used to predict room type, borough or neighbourhood, minimum nights, number of reviews, reviews per month, host listing count, and annual availability. Dummy coding was used to enter the categorical variables. The multicollinearity was checked by variance inflation factors, the normality and linearity were checked by residual plots, and homoscedasticity was checked by the constant variance plots. The geographic distribution of listings and neighbourhood-level price trends for New York City was also mapped using latitude and longitude.

2.10 Statistical Significance and Ethical Considerations

All statistical tests were two-tailed, and the p value < 0.05 was taken as significant. Where appropriate, results were presented as coefficients, model-fit statistics, confidence intervals, and effect size. The study used secondary data that was publicly available and did not include any direct interaction with humans. To ensure privacy, host names and other identifying information have been omitted from interpretation and reporting.

3. Results

3.1 Dataset Screening and Analytical Sample

The original data set was an Airbnb Open Data for the New York City area, which started with 48,895 Airbnb listings and 16 variables. Of the 205 listings with a recorded nightly price, 11 were excluded during screening data because the nightly price they reported was US$0, which can be considered an invalid price for pricing analysis for the purpose of this report. The last analytical sample comprised 48,884 listings in five boroughs and 221 neighbourhoods in NYC. There were no duplicate listing identifiers found. There were 10,051 listings that had no reviews recorded, and 38,833 listings with one or more. The number of reviews per month and the last review that were missing were primarily for listings that had not received any reviews. The composition of the final sample is given in Table 1.

Table 1. Distribution of Airbnb listings by borough, room type, and review status

Variable	Category	n	Percentage (%)
Borough	Manhattan	21,660	44.31
	Brooklyn	20,095	41.11
	Queens	5,666	11.59
	Bronx	1,090	2.23
	Staten Island	373	0.76
Room type	Entire home/apartment	25,407	51.97
	Private room	22,319	45.66
	Shared room	1,158	2.37
Review status	Reviewed	38,833	79.44
	Not reviewed	10,051	20.56

As seen in Table 1, Manhattan and Brooklyn combined made up about 85% of all listings. The majority of rooms were in whole houses or apartments, closely followed by Private rooms. Only 2.37% of the sample were shared rooms.

3.2 Descriptive Characteristics of Airbnb Listings

Table 2 presents the descriptive statistics for price, minimum-night requirement, review activity, host listing concentration and annual availability.

Table 2. Descriptive statistics of continuous listing characteristics

Variable	N	Mean	SD	Median	Q1	Q3	Minimum	Maximum
Nightly price (US$)	48,884	152.76	240.17	106.00	69.00	175.00	10	10,000
Minimum nights	48,884	7.03	20.51	3.00	1.00	5.00	1	1,250
Number of reviews	48,884	23.27	44.55	5.00	1.00	24.00	0	629
Reviews per month	48,884	1.09	1.60	0.37	0.04	1.58	0	58.50
Host listings count	48,884	7.14	32.96	1.00	1.00	2.00	1	327
Availability in 365 days	48,884	112.78	131.63	45.00	0.00	227.00	0	365

The average amount charged per night was $152.76, while the median amount charged per night was significantly lower at $106.00. The difference suggests that the price distribution had a positive skew due to a smaller number of high price listings. Half of the properties listed ranged between US$69 and US$175 per night. The average minimum-stay, which shows the value in the middle of the list, was three nights, but the maximum of 1,250 nights is a clear sign of some very unusual listings. The average host had one listing, with some hosts having up to 327 listings, indicating the presence of professional or commercial Airbnb operators.

3.3 Distribution of Nightly Prices

The distribution of prices for the nights is depicted in Figure 1. The graph shows listings to the 99th price percentile in the USA of US$799 to make the graph easier to follow visually.

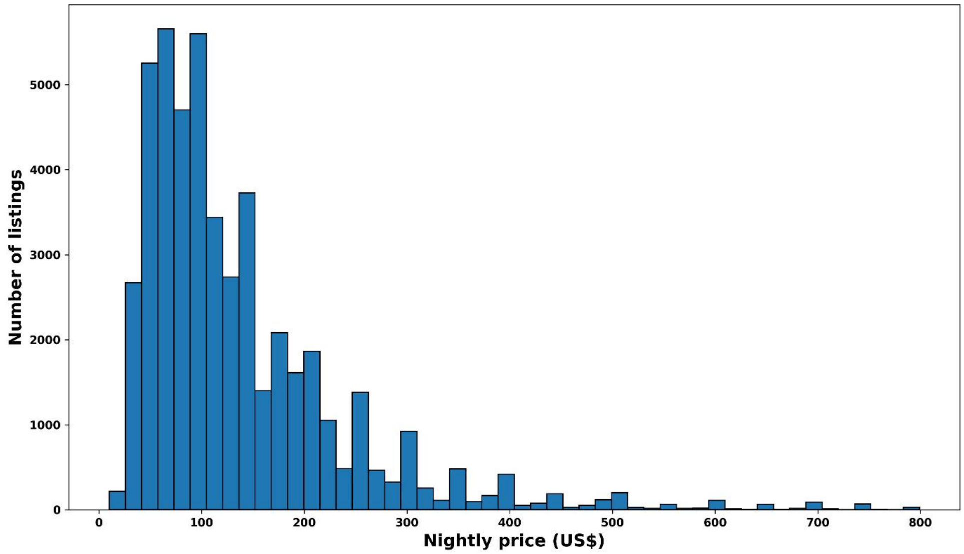

Figure 1. Distribution of Airbnb nightly prices in New York City

Figure 1 shows that the majority of listings were priced around the US$200/night mark. There were a relatively small number of premium and luxury listings with significantly higher price points and a long right tail on the distribution. The observed non-normality justified the choice of median-based summaries and non-parametric tests and the natural log transformation of price for the regression analysis.

3.4 Pricing Patterns by Room Type

Table 3 shows that there were significant differences between the three types of rooms for nights stayed.

Table 3. Airbnb nightly prices according to room type

Room type	n	Mean price (US$)	SD	Median price (US$)	Q1	Q3
Entire home/apartment	25,407	211.81	284.05	160	120	229
Private room	22,319	89.81	160.22	70	50	95
Shared room	1,158	70.25	101.77	45	33	75

Private and shared rooms had median prices of US$70 and US$45, respectively, whereas entire home/apt had a median price of US$160. The Kruskal – Wallis test revealed that there were significant differences in nightly rates for the different room types, H = 22,414.84, $p < 0.001$. Figure 2 displays the distribution of prices in each room category.

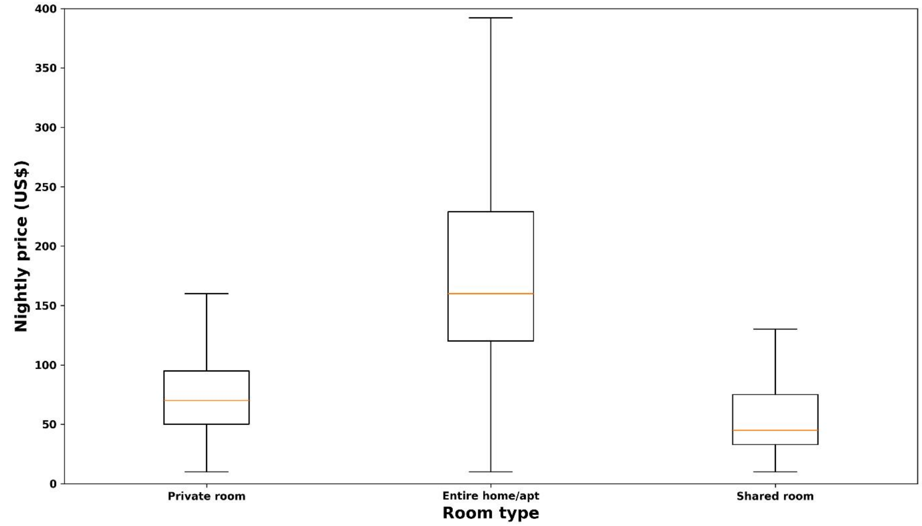

Figure 2. Distribution of nightly prices across Airbnb room types

Overall, full homes or apartments cost more than private and shared rooms, as shown in Figure 2. The median price and the smallest range of prices around the median were for shared rooms.

3.5 Borough-Wise Pricing Patterns

While Table 4 above shows that the average prices for Airbnb were relatively similar across the five boroughs of New York City, there was significant variation within each borough.

Table 4. Borough-wise distribution of Airbnb nightly prices

Borough	n	Mean price (US$)	SD	Median price (US$)	Q1	Q3
Manhattan	21,660	196.88	291.39	150	95	220
Brooklyn	20,095	124.44	186.90	90	60	150
Staten Island	373	114.81	277.62	75	50	110
Queens	5,666	99.52	167.10	75	50	110
Bronx	1,090	87.58	106.73	65	45	99

The mean and median price of a night's stay were the highest in Manhattan, at US$150. The median price in Brooklyn was US$90, second only to the borough of Manhattan. The median rent per night for the Bronx was US$65, the lowest of any of the boroughs surveyed. The Kruskal-Wallis test showed that the price varied significantly between boroughs $H=7{,}023.12$, $p<0.001$.

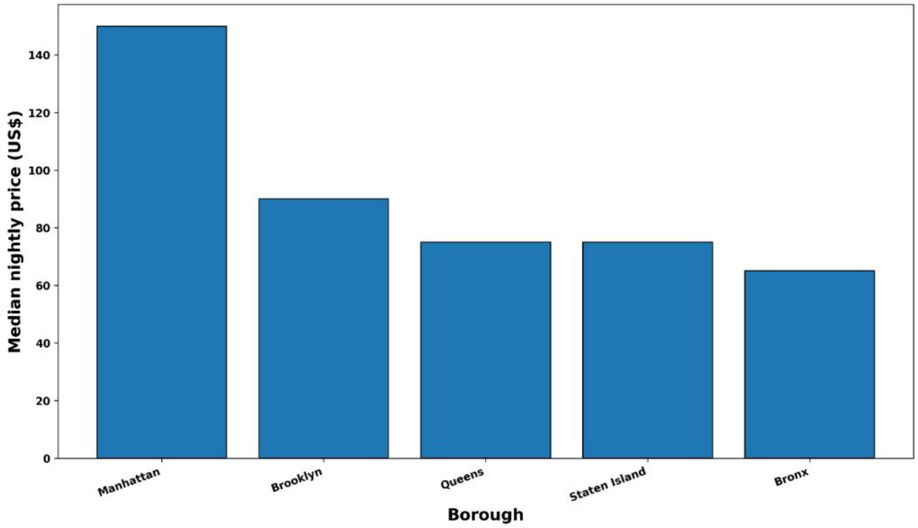

Figure 3. Median Airbnb nightly price by New York City borough

The median price was clearly higher than in the other boroughs, particularly Manhattan, as illustrated in Figure 3. The median price for Brooklyn was relatively high, between the other boroughs, while the median prices in Queens, Staten Island and the Bronx were found to be relatively low.

3.6 Correlation Between Listing Characteristics and Price

Spearman correlation was conducted due to the lack of normality of several continuous variables. Table 5 shows the correlation coefficients.

Table 5. Spearman correlations among Airbnb price and listing characteristics

Variable	Price	Minimum nights	Number of reviews	Reviews/month	Host listings	Availability
Price	1.000					
Minimum nights	0.101***	1.000				
Number of reviews	−0.055***	−0.175***	1.000			
Reviews per month	−0.060***	−0.247***	0.852***	1.000		
Host listings count	−0.106***	0.064***	0.056***	0.096***	1.000	
Availability in 365 days	0.086***	0.076***	0.237***	0.298***	0.407***	1.000

Price had a weak positive relationship with minimum nights, rs=0.101, and annual availability, rs=0.086. Weak negative correlations were observed between price and the number of reviews, rs=−0.055, reviews per month, rs=−0.060, and host listings count, rs=−0.106.

The best correlation was found between the number of reviews and reviews per month, rs = 0.852. There was also a moderate positive correlation with annual availability rs = 0.407 for host listing count. The entire correlation pattern is shown in Figure 4.

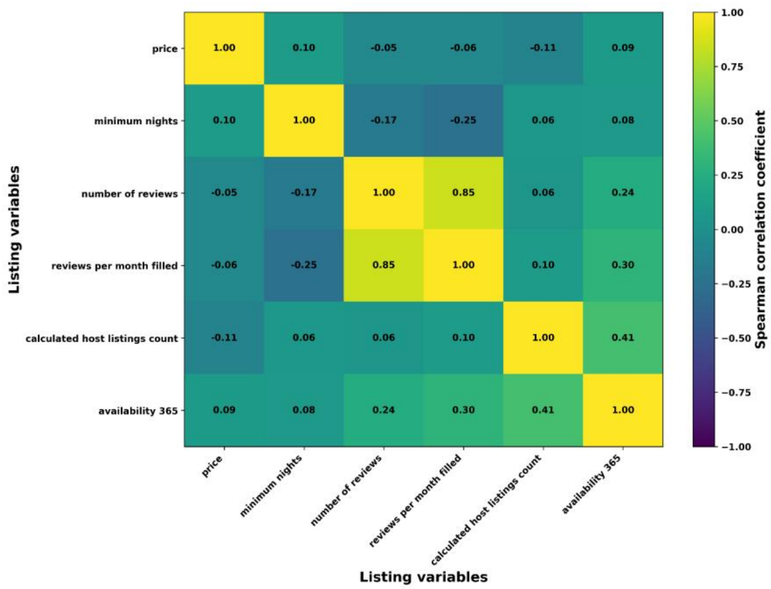

Figure 4. Spearman correlation matrix of Airbnb listing variables

Most direct correlations with price were very low, as illustrated in Figure 4. It implies that the variance in price rates is a lot more driven by room type and location than by review activity and availability, and that's a big difference.

3.7 Multivariable Regression Analysis

The dependent variable was the natural log of the nightly price, and a multiple linear regression model was estimated. The reference categories were chosen as a private room and Brooklyn. Heteroscedasticity-robust HC3 standard errors were used. The overall model was statistically significant, with an F=4,039.63 and p<0.001, which accounted for an R2 of 57.3% and an adjusted R2 of 57.3% of the variation in log-transformed nightly price. Table 6 reports the results of the regression analyses.

Table 6. Multiple regression analysis predicting log-transformed Airbnb price

Predictor	B	Robust SE	95% CI	Estimated price effect (%)	p-value
Entire home/apartment[1]	0.783	0.005	0.773 to 0.792	+118.74	<0.001
Shared room[1]	−0.394	0.019	−0.430 to −0.357	−32.53	<0.001
Bronx[2]	−0.253	0.015	−0.283 to −0.224	−22.36	<0.001
Manhattan[2]	0.322	0.005	0.312 to 0.332	+37.97	<0.001

Queens²	−0.133	0.007	−0.147 to −0.118	−12.41	<0.001
Staten Island²	−0.255	0.029	−0.312 to −0.198	−22.48	<0.001
Minimum nights	−0.00185	0.00031	−0.00246 to −0.00124	−0.18 per night	<0.001
Number of reviews	−0.00057	0.00005	−0.00068 to −0.00047	−0.06 per review	<0.001
Reviews per month	−0.0121	0.0017	−0.0154 to −0.0087	−1.20 per unit	<0.001
Host listings count	0.00004	0.00007	−0.00008 to 0.00017	+0.00	0.495
Availability in 365 days	0.00073	0.00002	0.00069 to 0.00077	+0.07 per day	<0.001

Once the other listing factors were factored out, the price of the entire home/apt was estimated to be around 118.7% more than private rooms. In contrast, shared rooms were approximately 32.5% less expensive than private rooms. The estimated Manhattan listing price was about 38.0% higher than the corresponding price in Brooklyn. The price of listings in the Bronx, Queens and Staten Island was around 22.4%, 12.4%, and 22.5% lower than Brooklyn listings, respectively. Minimum nights, number of reviews and reviews per month were statistically significant negative correlations, but they were relatively small. There was a small positive relationship between annual availability and price. There was no independent relationship of the number of hosts listed with price (p=0.495).

3.8 Spatial Distribution of Airbnb Listings and Prices

To show the geographic spread of listings by latitude and longitude, Figure 5 displays the listings by latitude and longitude. To avoid the domination of a small number of extreme values in the price scale, nightly prices were capped at the 99th percentile in the visualisation.

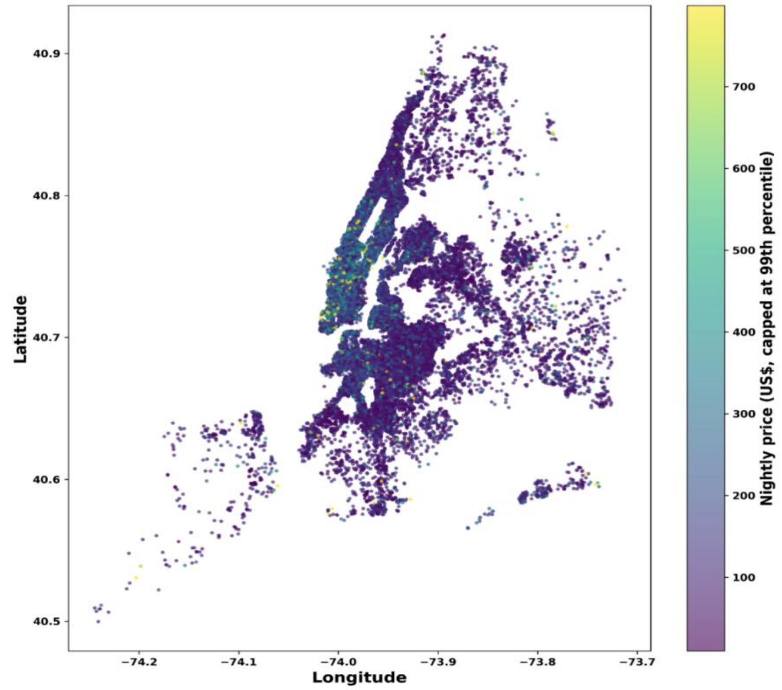

Figure 5. Spatial distribution of Airbnb listings and nightly prices across New York City

Figure 5 shows that Airbnb listings were highly concentrated in Manhattan and west Brooklyn. The higher-priced listings tended to be clustered near the tourist and commercial hubs in central Manhattan, and in the neighbourhoods where they are. Generally, the advertised price was lower, and the number of listings lower in the outer boroughs of Queens, the Bronx, and Staten Island.

3.9 Summary of Major Findings

Results indicated that room type and location are the main factors that differentiate the price patterns of Airbnb listings within NYC. Whether it was a whole home or an apartment, private and shared rooms were significantly less expensive than those in Manhattan, and whole home prices were much higher than shared room prices. Review activity, minimum nights, host listing concentration, and availability were all found to have a statistically significant relationship with price; however, these relationships were generally low. The model with multiple variables accounted for about 47.3% of the variation in the log-transformed listing prices, suggesting that the available listing characteristics were a good but incomplete explanation of the listing prices. Any remaining variation in price may be due to other variables not included in the data set, for example the number of bedrooms, bathrooms, amenities, accommodation capacity, property quality and distance from tourist attractions.

4. Discussion

This study explored the relationship between the characteristics of Airbnb listings and the pricing patterns of nights available for short-term rentals. The results revealed that room type and geographical location were the strongest factors affecting price, while minimum night requirement, review activity, host listing concentration and annual availability had a less significant effect. Private and shared rooms were significantly less expensive than entire homes or apartments, and the highest prices were found for Manhattan apartments. The regression model accounted for almost half of the variation of log-transformed prices so there was a meaningful amount of pricing behaviour available to be captured by the available variables.

The results of the strong effect of the room type are consistent with previous research showing that the type of accommodation is a key factor in the price formation of Airbnb. The private property offers more privacy, space and flexibility that is conducive to a higher willingness to pay compared to private or shared rooms. In addition, structural listing attributes have been found to affect listing prices and revenues (Sainaghi et al., 2021). In addition, quantile-based research indicates that the impact of Listing attributes is different in the low-price, medium-price, and high-price segments, and that in the high price segment, some attributes become more important. (Moreno-Izquierdo et al., 2020). So, the room type is not just a physical characteristic of the room, but also a market segment.

Price was also heavily influenced by the location. Rental rates for Manhattan properties were much higher than in other areas of Brooklyn, the Bronx, Queens, and Staten Island. This is consistent with the study results indicating that local demand, neighbourhood prestige, accessibility and proximity to attractions are significant factors that affect the price of Airbnb listings (Chica-Olmo et al., 2020). Spatial dependence could also exist because hosts can monitor the prices of nearby competitors and respond accordingly. This price mimicking may vary by multi-host and single-host operators, creating localised pricing clusters (Boto-García et al., 2021). The neighbourhood's appeal, combined with the way house owners behave, thus explains the concentration of high-priced listings.

The price was negatively associated with review-related variables with statistically significant but weak relationships. This could be because lower-priced listings get more bookings and thus more reviews. The sharing platforms charge for sharing based on information regarding the transaction (including listing features) and the partner (including the host's reputation and prior guest comments; Engin & Vetschera, 2022). The impact of trust indicators on willingness to pay can be reduced after considering the type and location of the room (Arvanitidis et al., 2022). The results thus indicate that while reputation is important, it is not more important than the basic features of the accommodation.

The number of hosts, which was not of itself significant in the regression model, has been found to differ in earlier research between individual and professional hosts and is likely to use different pricing strategies. Professional hosts may implement Revenue Management Systems, Dynamic pricing and Portfolio-level decisions (Abrate et al., 2022). Other factors that could affect pricing include experience, size of operation, and strategic positioning (Li et al., 2026). Nevertheless, the number of listings alone is not a reliable indicator of professionalism, as it will not measure the standards of service, the commercial intensity, quality of management, or the use of pricing software.

The price variation is not explained, which may indicate the relevance of the missing attributes of the listings. The price estimation might be enhanced by amenities, property quality, accommodation capacity, interior features and textual description. In the U.S. and Canada, amenity information has been found to impact perceived quality among Airbnb markets (Chattopadhyay & Mitra, 2024). Price indicators may also vary depending on the market conditions in the area under study and the analytical technique employed to convey the listings, which are not monoliths, but may be heterogeneous (Contu et al., 2023). Methodological research also cautions against the use of Airbnb hedonic models because they are sensitive to variable selection, spatial dependence, and sample construction (Faye, 2021).

The results further validate the use of predictive modelling. Machine-learning methods can detect nonlinear relationships and interactions that regression would not detect. Sentiment analysis and features related to sustainability have been successfully integrated into models that have shown valuable price-prediction capabilities (Alharbi, 2023). Ensemble frameworks can also perform well without the detailed amenity variables (Ghosh et al., 2023), and comparative studies have validated the effectiveness of machine-learning algorithms in estimating Airbnb rental prices (Lektorov et al., 2023). However, interpretability is also relevant as it is important for the host and policy makers to know what is driving the difference in the predicted prices.

In sum, the costs of Airbnb accommodation were largely influenced by accommodation type and spatial context, whereas reputation and operational variables had supporting roles. Results can be used to compare prices with other properties that are similar and can be used to inform policy makers so they can understand geographic concentration and professionalisation. The remaining price variation should be explained in the future with the help of amenities, capacity, occupancy, seasonal demand and neighbourhood socioeconomic conditions.

5. Conclusion

Using a large cross-section of data, this study measured Airbnb listing characteristics and pricing trends in the short-term rental market in the city of New York. The results showed that within the same room type, the price of a night by location is quite different. Private and shared rooms in Manhattan were invariably more expensive than their counterparts in Brooklyn, Queens, the Bronx, and Staten Island, and entire homes or apartments were significantly more expensive than the private and shared room counterparts. The findings are consistent with other scholars who found that the type and location of accommodation are the major factors affecting Airbnb pricing. The other activities, host listing concentration, and annual availability had relatively low correlations with price. Some of these factors were statistically significant, but their effect was small when room type and borough were controlled for. The results of the regression model showed a significant amount of the variance in the prices of the log-transformed variables; there was still some variance that was not accounted for. This indicates that other characteristics, including amenities, property size, number of bedrooms, number of bathrooms, number of accommodations, interior quality, seasonal demand and proximity to tourist attractions, might also influence listing prices. In general, this study points to the importance of listing-level analysis in the context of price formation in short-term rental markets. The results can help hosts to price their services more competitively, help travellers understand market variations.

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