



Consecutive Renting and Other Factors Influencing the Block Behaviors of Airbnb Hosts

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Abstract. This paper examines how short-run rental activity influences hosts' calendar-blocking decisions on Airbnb. Using listing-level daily information, the analysis studies whether recent rental sequences are systematically associated with subsequent availability choices. The results show that consecutive renting is associated with a lower likelihood of blocking and that blocking behavior varies across time and listing characteristics. These findings suggest that effective platform supply is shaped by day-to-day host behavior rather than fixed property inventories.

Keywords: Airbnb; short-term rentals; host behavior; platform supply; availability; peer-to-peer platforms; shared economy

1 Introduction

Different from traditional hotel industry, Airbnb and other peer-to-peer short-term rental platform aggregate capacity from thousands of small hosts who share their properties for profit, and these hosts decide that their listings are available or not on each day. Because availability directly determines the platform's effective supply, understanding why hosts choose to open or close their listings is essential for interpreting Airbnb's role in urban accommodation markets.

While existing research has extensively examined Airbnb's impacts on hotels, housing markets, and consumer welfare, far less is known on the supply side of Airbnb, especially hosts' behaviors that decide how many shared properties on platform are actually available in market. In particular, calendar blocking—when hosts mark dates as unavailable for personal, strategic, or operational reasons—remains understudied despite directly reducing supply. Prior work has linked blocking to pricing or fixed listing characteristics, but has not considered blocking as a dynamic decision that may respond to recent rental activity or vary systematically across seasonal time patterns.

To address this gap, the present analysis examines how recent rental conditions relate to next-day blocking decisions. Using daily panel data for Airbnb listings in New York City from 2014 to 2016, the study relates blocking outcomes to a binary measure of consecutive renting, along with listing features and time effects, through pooled and logit regression models. Complementary descriptive methods are used to compare

blocking probability across rental status and to illustrate heterogeneity across property features.

This study contributes to the literature in three ways. First, it identifies dynamic behavioral factors that shape hosts' blocking decisions, exceeding static interpretation of availability. Second, it documents heterogeneity in blocking behavior across listing types and seasonal conditions. Third, by analyzing a multi-year panel from one of Airbnb's largest and most contested markets, the study provides evidence on how micro-level availability choices shape platform-level supply dynamics.

After the Introduction, the paper is organized as follows: Section 2 reviews related literature; Section 3 describes the data; Section 4 presents the empirical framework and main results, including heterogeneity diagnostics; Section 5 discusses implications; and Section 6 concludes.

2 Literature Review

Over the last decade, peer-to-peer short-term rental platforms have reshaped how travelers access lodging. Among these platforms, Airbnb has expanded from a small-scale project into a major player in urban tourism and accommodation markets. Its growth has intensified debates over tourism development, competition in the accommodation industry, and housing use in major cities. The core of this transformation is a distinctive supply structure: instead of relying on large, capital-intensive real estate assets, capacity of platforms like Airbnb is provided by thousands of small hosts who decide to open their properties for rental or not on each day based on their own conditions.

This decentralized structure forms supply that differs fundamentally from traditional hotel. While the hotel capacity is largely fixed in the short run, the availability of Airbnb listings can adjust in the short term, as individual hosts choose to open their properties or not. Building on this distinction, recent economic research shows that peer-host supply is highly elastic—around three times as elastic as hotel supply—and tends to grow most in cities and periods where demand is high and hotel capacity is constrained [1]. In such environments, the expansion of Airbnb supply reduces hotels' pricing power and lowers their revenues, especially significant during peak-demand events [2].

Beyond these competitive effects, the flexibility of host-driven supply has been linked to broader efficiency gains in accommodation markets, particularly during peak-demand periods [1]. This evidence suggests that Airbnb's effective supply is generated through hosts' short-run participation decisions, making it important to understand factors—such as date blocking—that restrict or expand platform availability.

In line with this reasoning, existing research shows that changes in Airbnb supply have measurable effects on accommodation markets and urban housing outcomes. Studies of hotel performance document that increased Airbnb activity is associated with reduced hotel revenues and changes in pricing behavior, while evidence from housing markets indicates that short-term rental activity is capitalized into local housing prices and rents [3, 4].

Together, these studies underscore that Airbnb's market impacts critically depend on how much supply hosts choose to provide at any given time. This reinforces the

importance of understanding availability decisions—particularly the use of calendar blocking—as key determinants of platform-level supply.

At the host level, research examining host behavior on Airbnb highlights substantial heterogeneity in how hosts price, manage, and operate their listings. Evidence from Corsica shows that professionally registered hosts systematically charge higher prices than opportunistic hosts, with the price premium widening during peak seasons and largely disappearing off-peak [5]. This pattern suggests that professional hosts perceive greater pricing opportunities in high-demand periods and adjust their strategies accordingly.

Related work examines the relationship between performance outcomes and operational choices. Using data from Milan and Rome, Abrate et al. find that revenue outcomes and pricing variability tend to increase with hosts' degree of professionalization [6]. Their analysis also documents a positive association between revenue performance and the share of dates that hosts block or mark as unavailable, indicating that calendar management is an integral component of hosts' operational strategies. Overall, the literature portrays hosts as strategic suppliers whose behaviors vary across contexts and over time. However, existing research has paid limited attention to calendar blocking as a behavioral outcome, despite the fact that availability decisions are central to determining the effective supply of Airbnb listings.

Existing work typically incorporates blocked dates into pricing or revenue models rather than treating blocking itself as a research object. One study shows that hosts often block dates for reasons that are not directly observable in scraped data, and that blocked dates can arise from personal use, operational constraints, or hybrid business models involving multiple platforms [7]. This work also highlights that blocked and booked dates are frequently difficult to distinguish in public data, reinforcing the need for datasets that reliably separate unavailability from realised demand.

Despite these contributions, prior research has not examined how blocking behavior responds dynamically to recent rental activity, nor has it linked blocking to time related patterns like seasonality. Existing studies rely largely on cross-sectional or low-frequency measures of availability, leaving day-to-day decisions unexplored. Addressing this gap, this study examines whether consecutive renting is associated with next-day blocking decisions and how this relationship varies across listing characteristics and time.

3 Data Description

This study uses two datasets from AirDNA. The primary analytical dataset is a listing-day panel covering all active Airbnb properties in New York City from 2014 to 2016. For each listing, the dataset reports the calendar status (available, booked, or blocked), daily price, reservation identifiers on each date. Such structure is well suited for building variables representing the rental dynamics on each listing, and the host's blocking behaviors. To summarize the structural characteristics of the shared property market, the analysis also draws on a listing-level snapshot, which includes 120,466 listings and reports static features such as listing type, unit size, and published nightly rate. After

merging daily records with property attributes and removing incomplete observations, the final panel contains approximately 47 million listing-day entries.

The snapshot dataset is introduced, because it provides an overview of the structural composition of Airbnb supply in New York City. Stable attributes in this dataset can be used for meaningful descriptive plots which will not change in the short run or be influenced by seasonal patterns. As shown in **Figure 1**, the market is dominated by small units, with entire homes, private rooms, and shared rooms forming the three major listing categories.

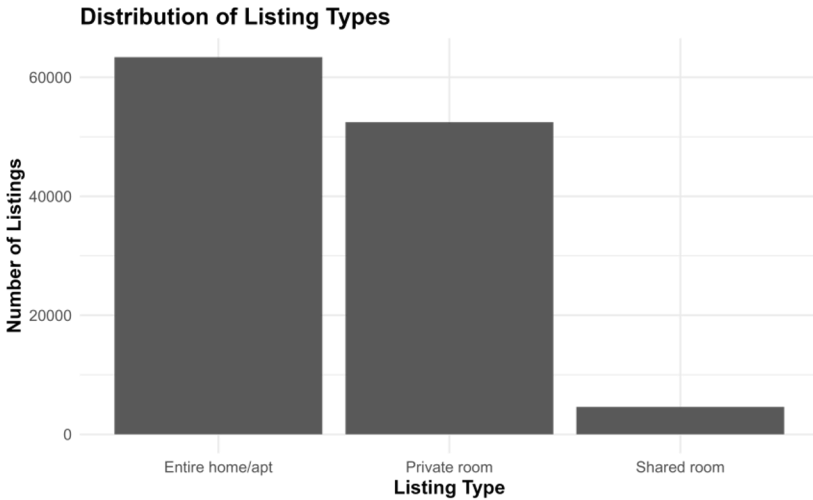


Fig. 1. Distribution of listing types among 120,466 Airbnb properties active on November 2, 2016. Entire homes comprise 52.6% of listings, private rooms 43.6%, and shared rooms 3.8% (AirDNA snapshot).

The number of bedrooms and bathrooms in each property exhibits very limited variation—over 74% of listings have one bedroom and 85% have one bathroom—indicating that most Airbnb units resemble small urban apartments rather than large vacation houses.

Nightly prices, however, display much greater dispersion. The raw price distribution is strongly right-skewed, with a median rate of \$129 and a long upper tail. This motivates the use of the log-transformed price measure, which produces a more symmetric distribution that aligns better with regression assumptions. **Figures 2** and **Figure 3** show that price levels differ sharply across listing types: entire homes are consistently more expensive than private and shared rooms, and the separation between categories becomes especially clear after log transformation.

To examine how recent rental activity influences availability decisions by hosts, the analysis constructs two key variables from the merged listing-day panel dataset. The first variable, consecutive renting, captures whether a listing is at the end of consecutive rented days. It equals 1 when the current and previous days are both booked, while the

following day is not booked. This indicator identifies the “completion” of a rental sequence, allowing the analysis to focus on hosts’ decisions immediately after a stay.

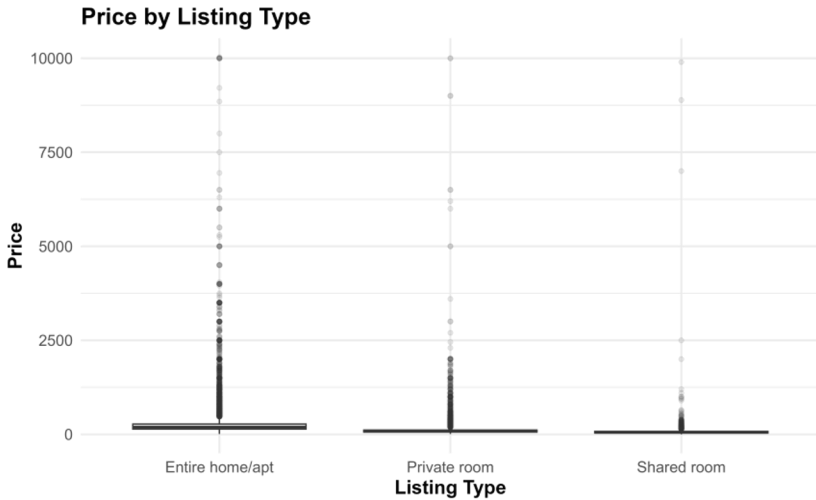


Fig. 2. Boxplot of published nightly prices by listing type. Entire homes are the most expensive (median \approx \$195), followed by private rooms (\approx \$83) and shared rooms (\approx \$52). Price distributions are heavily right-skewed.

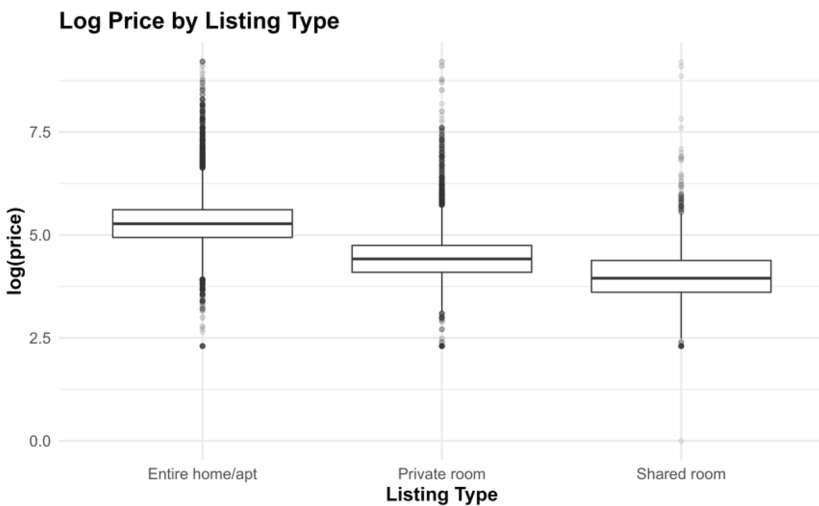


Fig. 3. Log-transformed nightly prices by listing type. The transformation produces a more symmetric distribution and highlights clear price segmentation across listing types. Log price is used in the regression analysis.

The second variable, blocked next, is constructed to measure host availability behavior. It equals 1 if the listing is marked as unavailable (“blocked”) on the following

day. Unlike booked status, which is determined by consumers, blocking decisions are made by hosts, so this variable directly represents host-initiated supply reductions. Take together, the two variables make it possible to test whether hosts are more likely to close their calendars immediately after a stay concludes—for reasons such as cleaning needs, rest periods, or personal use.

Both variables are generated by ordering each listing’s panel records by date, applying lag and lead operations to the daily Status field, which classifies each day as available (“A”), booked (“R”), or blocked (“B”). This structure allows the dataset to capture the dynamic sequence of rental activity and availability changes at the listing-day level, forming the basis for analyzing how hosts adjust supply in response to recent rental patterns.

4 Regression Analysis

4.1 Baseline Logit Model

Firstly, logistic regression is used to examine the relationship between hosts’ blocking behavior and the listings’ recent rental conditions. It is appropriate in this context because the outcome variable, blocked_next, is binary and exhibits highly unbalanced probabilities across tens of millions of observations. A logit specification ensures that predicted values remain within the [0,1] range, models the non-linear relationship between covariates and event probability, and provides interpretable odds ratios that align well with behavioral decisions such as opening or closing availability. The baseline specification is:

$$\Pr(\text{blocked_next}_{it} = 1) = \text{logit}^{-1}(\alpha + \beta \text{consec_rented}_{it}),$$

where

- blocked_next_{it} indicates whether listing *i* becomes blocked by the host on day *t*+1,
- consec_rented_{it} identifies the end of a multi-day rental sequence on day *t*.

Estimated on all 47 million listing-day observations, the model produces the coefficients shown in **Table 1**.

Table 1. Baseline Logit Regression Results. *Dependent variable: blocked_next*

Variable	Estimate	Std. Error	Odds Ratio
Intercept	-0.4476***	0.000303	0.6392
consec_rented	-0.1235***	0.001682	0.8838

Notes: Standard errors are independent and identically distributed (IID). Stars indicate statistical significance: *** *p* < 0.001, ** *p* < 0.01, * *p* < 0.05.

4.2 Pooled Logit Model with Listing Characteristics and Time Effects

While the simple logit model establishes a strong association between consecutive renting and next-day blocking, a richer specification is required to account for structural heterogeneity across listings and temporal variation in platform activity. To isolate the relationship of interest and reduce potential omitted-variable bias, the analysis incorporates a set of listing-level and time-varying controls.

Listing characteristics include the number of bedrooms and bathrooms, which capture unit size and capacity, and a set of indicators for listing type (entire home/apt, private room, shared room). These features reflect meaningful differences in host operations and guest demand that may also influence availability management. Pricing is controlled for using the logarithm of the published nightly rate, which mitigates skewness in the distribution of prices and serves as a proxy for underlying property quality and neighborhood attributes.

Seasonal and annual variation are captured through month and year indicators. These controls absorb broad shifts in platform demand, regulatory environments, and host behavior that are unrelated to listing-level decisions. Incorporating these factors yields the following pooled logit model:

$$\Pr(\text{blocked_next}_{it} = 1) = \text{logit}^{-1}(\alpha + \beta \text{consec_rented}_{it} + \gamma_1 \text{Bedrooms}_i + \gamma_2 \text{Bathrooms}_i + \gamma_3 \log(\text{Price}_{it}) + \delta \text{Listing.Type}_i + \tau_{\text{Year}} + \kappa_{\text{Month}})$$

Given the scale of the dataset, the pooled logit model is estimated using a common large-dataset strategy. The panel is divided into five non-overlapping groups based on Property.ID; the model is fitted separately within each group, and the resulting coefficients are aggregated using inverse-variance weighting. This procedure retains all observations while improving numerical stability and computational feasibility in high-volume settings.

Combined coefficients and standard errors are reported in **Table 2**.

Table 2. Pooled Logit Regression Results. *Dependent variable: blocked_next*

Variable	Estimate	Std.Error	Odds Ratio
Intercept	0.9624***	0.00357	2.618
consec_rented	-0.1485***	0.00170	0.8620
Listing.Type: Private room	-0.4983***	0.00080	0.6078
Listing.Type: Shared room	-1.2743***	0.00214	0.2796
Bedrooms	-0.0585***	0.00051	0.9432
Bathrooms	-0.0201***	0.00086	0.9801
log_price	-0.2518***	0.00064	0.7775

Notes: Standard errors are IID. Coefficients are combined across five subsamples using inverse-variance weighting. All models include year and month fixed effects. Pseudo $R^2 \approx 0.011$. Stars indicate statistical significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

4.3 Comparison of Model Estimates

The pooled specification provides a more comprehensive assessment of how consecutive renting relates to blocking behavior by incorporating listing characteristics and time effects. Across all five subsample estimations, the pooled models exhibit pseudo- R^2 values around 0.01, which is substantially higher than the value obtained from the simple logit model. This improvement reflects the contribution of structural heterogeneity and seasonal patterns in explaining variation in blocking behavior.

To assess the stability of the estimated coefficients, the pooled logit model is estimated separately on five non-overlapping subsamples constructed at the property level. This chunked estimation procedure serves as a form of cross-validation: coefficients are compared across subsamples to evaluate whether estimated effects are sensitive to the choice of estimation sample. As reported in **Table 3**, coefficient estimates are highly consistent across chunks in both sign and magnitude, with only modest variation. This stability indicates that the estimated relationship between consecutive renting and blocking behavior, as well as the effects of key control variables, is not driven by idiosyncratic subsamples or sampling variation.

Table 3. Cross-validation: Coefficients by Chunk

Term	Chunk 0	Chunk 1	Chunk 2	Chunk 3	Chunk 4
(Intercept)	1.0401	0.8856	0.8857	1.0382	0.9635
consec rented	-0.1481	-0.1463	-0.1255	-0.1462	-0.1768
Listing.TypePrivate room	-0.5021	-0.5016	-0.4719	-0.5271	-0.4893
Listing.TypeShared room	-1.3070	-1.2577	-1.2304	-1.2273	-1.3526
Bedrooms	-0.0699	-0.0535	-0.0370	-0.0707	-0.0614
Bathrooms	-0.0036	-0.0206	-0.0666	-0.0001	-0.0102
log_price	-0.2654	-0.2386	-0.2313	-0.2691	-0.2546
Year2015	0.0484	0.0566	0.0420	0.0490	0.0584
Year2016	0.0835	0.1105	0.0801	0.1019	0.1267
Month2	0.0104	0.0165	0.0148	0.0146	0.0124
Month3	0.0196	0.0169	0.0260	0.0205	0.0143
Month4	0.0357	0.0349	0.0431	0.0373	0.0317
Month5	0.0702	0.0698	0.0776	0.0851	0.0671
Month6	0.0983	0.0948	0.0942	0.1137	0.0964
Month7	0.0869	0.0892	0.0886	0.1037	0.0824
Month8	0.0757	0.0735	0.0719	0.0849	0.0696
Month9	0.1004	0.0968	0.0962	0.1047	0.0961
Month10	0.1078	0.0991	0.1043	0.1159	0.1044
Month11	0.0909	0.0861	0.0877	0.1046	0.0915
Month12	0.0699	0.0672	0.0628	0.0779	0.0759

Importantly, the coefficient on consecutive renting remains negative and highly significant in all specifications, and its magnitude is only moderately attenuated after controls are added. The consistency in sign and significance across the simple and pooled

models suggests that the estimated relationship is not driven by omitted property attributes or temporal confounders. A detailed interpretation is provided in Discussion Section.

4.4 Residual Plots

To further assess model adequacy, residual diagnostics are conducted using Pearson residual plots. Residual plots examine whether the difference between observed outcomes and model-predicted probabilities exhibits systematic patterns with respect to key explanatory variables. In a well-specified logistic regression, residuals should be centered around zero and should not display strong trends or heteroskedasticity across covariates.

Figures 4–6 plot Pearson residuals against consecutive renting status, log-transformed price, and unit size. Figure 4 uses boxplots to examine whether residual distributions differ systematically between consecutively rented and non-consecutive observations. Figure 5 plots residuals against log price to assess whether prediction errors vary with price levels, which would indicate model misspecification. Figure 6 presents boxplots by bedroom count, providing a diagnostic check on the linear specification of unit size in the pooled logit model.

Across these dimensions, residuals remain broadly centered and show no sharp discontinuities between groups. While mild curvature appears in the residuals with respect to price—particularly at the extremes of the distribution—such patterns are common in large-scale binary response models and do not indicate substantive misspecification. Overall, the residual plots support the adequacy of the pooled logit specification and suggest that the estimated relationships are not driven by systematic prediction errors tied to the main covariates.

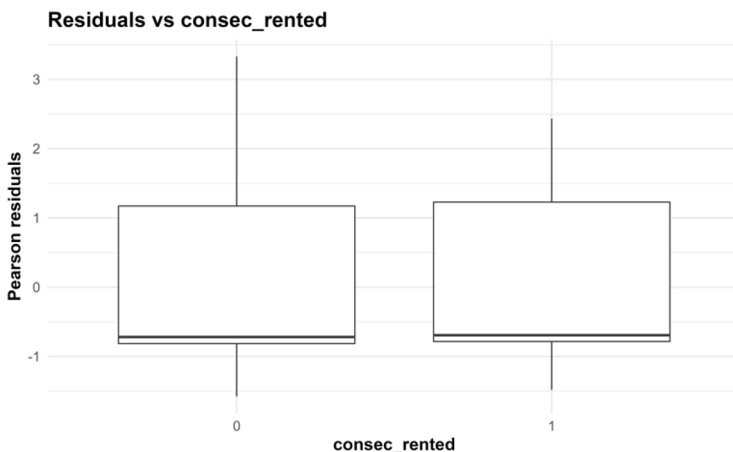


Fig. 4. Pearson residuals from the pooled logit model against the binary indicator for consecutive renting. Boxplots summarize the distribution of residuals separately for listings that are and are not in a consecutive-renting period.

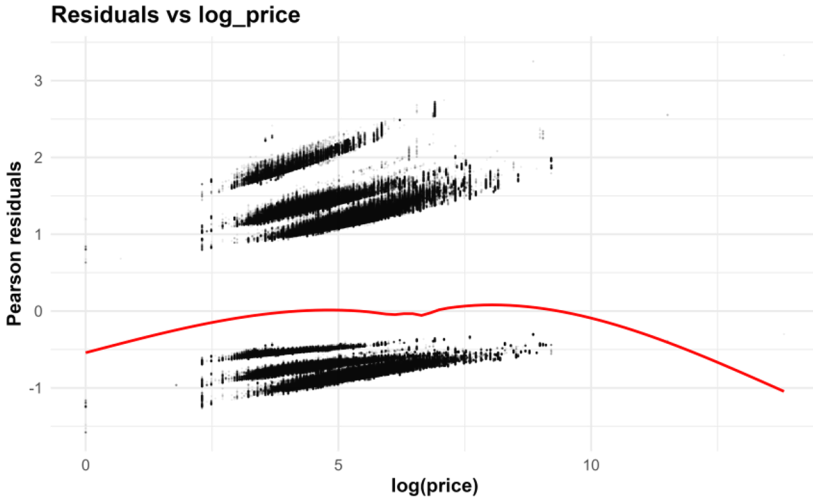


Fig. 5. Pearson residuals from the pooled logit model plotted against log-transformed nightly prices. A smoothed curve is overlaid to highlight potential nonlinear patterns.

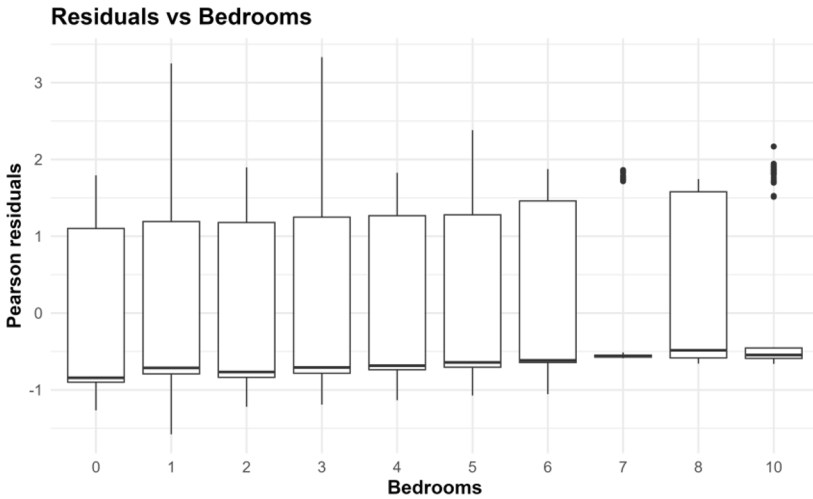


Fig. 6. Boxplots of Pearson residuals by bedroom count

5 Discussion

The empirical results provide consistent evidence that recent rental activity influences hosts' blocking decisions. In the simple logit model, the estimated odds ratio for `consec_rented` is approximately 0.88, implying that next-day blocking is about 12% less likely when a listing is rented on consecutive days. After accounting for listing charac-

teristics and time effects, the pooled model yields an odds ratio near 0.86, which corresponds to roughly a 14% reduction in the odds of blocking. In comparison, after structural and seasonal control variables are added, the effect becomes slightly stronger. This difference suggests that consecutive renting has an independent negative association with hosts' blocking behavior, and this relationship is not driven by confounding differences across properties or seasonal patterns.

Residual diagnostics support the robustness of these regression results. Pearson residual plots reveal no strong systematic patterns with respect to the main explanatory variables, including consecutive renting, price, and bedrooms. Residuals remain broadly centered across covariate values, suggesting that the pooled logit specification provides an adequate approximation to the blocking process and that the estimated effects are not driven by systematic model misspecification.

The results point to a behavioral mechanism in which recent rental activity influences hosts' short-run availability decisions. Listings that have been rented on consecutive days exhibit a lower probability of next-day blocking, consistent with a form of state dependence. When a listing is actively rented, its host's work consists of communicating with guests, maintaining the listing, and coordinating cleaning. Once a rental sequence is underway, the marginal effort required to continue renting is relatively low, so the host is more likely to continue making the listing available. By contrast, if the listing has not been rented for a while, hosts' willingness to host may decrease, or they feel greater uncertainty about future demands. These considerations increase the likelihood that a host temporarily blocks the calendar—hosts may put the property in self-use, address large maintenance tasks, improve facilities, or simply keep the listing unavailable until they are prepared to resume hosting.

The pooled model also reveals several meaningful associations between listing characteristics and blocking behavior. Higher-priced listings are less likely to be blocked, reflecting stronger demand, higher revenue potential, and potentially greater host professionalism. This financial incentive aligns with the pattern observed for consecutive renting: both factors suggest that hosts are less inclined to restrict availability when expected returns are high. Similarly, private rooms and shared rooms exhibit substantially lower blocking probabilities than entire homes, consistent with lower opportunity costs of hosting and fewer alternative uses for the property. Unit size also matters: listings with more bedrooms or bathrooms tend to have lower blocking rates, possibly because larger units appeal to groups or families whose trips are planned further in advance. Together, these structural patterns indicate that blocking behavior is shaped not only by recent rental dynamics but also by underlying economic and operational characteristics of each listing.

The estimated month and year effects further illustrate the temporal patterns underlying host behavior. Blocking probabilities are lowest in January and February and rise steadily throughout the calendar year, reaching their peak in September and October before declining again. This pattern reflects a clear seasonal cycle: hosts are most likely to restrict availability during the late-summer and early-fall months, probably because of personal travel, family events, or even the need to prepare children for the new school year can make hosting less convenient. The year indicators also show an upward trend, with blocking becoming progressively more common from 2014 to 2016. This growing

tendency may reflect tightening regulations, increased platform maturity, changes in host composition, or shifting expectations about market demand. In combination, these temporal effects highlight that blocking behavior is influenced not only by host readiness and listing characteristics but also by broader seasonal and annual dynamics.

These findings highlight the importance of considering calendar blocking when evaluating the effective supply of short-term rentals. Blocking removes potential inventory from the platform, and the analysis shows that hosts block their properties for multiple reasons, including short-run rental conditions, listing attributes, revenue considerations, and seasonal timing. Understanding which factors reduce blocking—such as sustained rental activity, higher expected revenue, or specific property types—helps clarify how hosts contribute to the elasticity and responsiveness of Airbnb supply across different market contexts. The regression results consistently indicate that listings that have been actively rented are less likely to be blocked on the following day, and this relationship persists after accounting for property characteristics and seasonal variation. The stability of this pattern indicates that blocking is not random or purely mechanical—it responds systematically to recent rental activity and to the structural features of the listing, reflecting behavioral and economic incentives rather than demand shocks alone.

6 Conclusion

This study examines how short-run rental activity relates to hosts' calendar-blocking decisions on Airbnb using a large-scale listing-day panel for New York City from 2014 to 2016. By merging property-level characteristics with daily availability records and constructing measures of consecutive renting and next-day blocking, the analysis provides a comprehensive and fine-grained empirical assessment of host-level supply behavior on a peer-to-peer accommodation platform. Methodologically, the paper applies both a simple logit model and a pooled specification with listing attributes and temporal controls, estimating the latter using a chunked estimation strategy to accommodate the full 47-million-observation panel.

Across all specifications, the results consistently show that recent rental activity reduces the likelihood of next-day blocking. In the simple model, consecutive renting is associated with about a 12% lower odds of blocking, while the pooled model—controlling for listing type, size, price, and seasonal factors—finds a slightly stronger effect of roughly 14%. Residual diagnostics further support the adequacy of the pooled specification, indicating that model predictions do not exhibit systematic deviations with respect to key explanatory variables. Beyond rental dynamics, the pooled model confirms systematic differences across property characteristics and time: larger and higher-priced units are less likely to be blocked, and blocking follows a clear seasonal pattern, peaking in late summer and early fall.

These findings foreground the behavioral processes underlying host availability. Rather than treating platform supply as fixed at the property level, the analysis demonstrates that supply is an outcome of day-to-day decisions shaped by rental momentum, listing features, and seasonal conditions. This perspective aligns with the broader view

in the literature that Airbnb's flexible, host-driven supply plays a central role in shaping market outcomes, from price competition with hotels to consumer welfare.

Despite its strengths, the study has several limitations. First, although the dataset distinguishes between booked and blocked dates, it cannot separate the motivations for blocking—such as personal use, maintenance, regulatory constraints, or strategic withholding. Second, the analysis focuses on New York City, a highly regulated and tourism-dense market, which may limit generalizability to other cities with different regulatory environments or host compositions. Third, the observational nature of the data prevents strong causal identification; while the results document robust associations, future work could incorporate quasi-experimental variation, such as local shocks or policy changes, to better isolate causal mechanisms.

These limitations also point toward promising avenues for future research. Detailed host-level surveys or platform-provided metadata could help distinguish types of blocking behavior and identify which forms are most responsive to rental activity. Comparative studies across multiple cities could clarify how regulatory regimes mediate blocking decisions or interact with host professionalization. Structural or dynamic models of host decision-making could further illuminate how expectations, pricing strategies, and opportunity costs shape day-to-day availability. Finally, future work could examine how blocking behavior aggregates to platform-level supply elasticity and affects competition with hotels during peak periods.

Overall, this study contributes to the understanding of peer-to-peer accommodation platforms by providing large-scale evidence on how recent rental sequences influence next-day availability decisions. By documenting the behavioral dynamics that underpin calendar blocking, the analysis provides new insight into host participation patterns and highlights the importance of short-run supply responsiveness in interpreting Airbnb's broader accommodation and housing market impacts.

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