Modern Economy, 2024, 15, 442-473
https://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

Introduction of Sharing Economy Based on "The Value of Flexible Work: Evidence from Uber Drivers"

Freya Huang

University of Washington, Seattle, Washington, USA
Email: freya725188@gmail.com

How to cite this paper: Huang, F. (2024). Introduction of Sharing Economy Based on "The Value of Flexible Work: Evidence from Uber Drivers". *Modern Economy, 15,* 442-473.
https://doi.org/10.4236/me.2024.154023

Received: January 21, 2024
Accepted: April 27, 2024
Published: April 30, 2024

Abstract

This extensive research paper delves into the sharing economy, focusing primarily on the popular platform, Airbnb. The sharing economy has become a transformative force in our society, driven by innovative technologies that enable peer-to-peer interactions, flexible work arrangements, and efficient use of resources. The essay starts by exploring the basic principles of the sharing economy, underscoring the importance of flexibility and efficiency in a dynamic marketplace where shared access prevails over ownership. Fixed first part of the paper closely examines Uber, highlighting its unique model that grants drivers exceptional flexibility in shaping their work schedules. It delves into the labor supply patterns of Uber drivers, comparing them with traditional employees, and uncovers the complementarity between Uber driving and conventional employment. For the second section, the paper explores Airbnb, emphasizing how it has disrupted the traditional hotel industry by providing travelers with access to distinctive lodging experiences. It investigates how Airbnb collaborates with and challenges traditional hotels, exploring factors like price dynamics and property-blocking behavior. The research extends to logistic regression analysis, providing insights into the determinants of Airbnb status categories and pricing. Supplementary analyses aim to gain a deeper understanding of property-blocking behaviors and supply curve dynamics within Airbnb. In conclusion, this paper offers a thorough examination of the sharing economy, highlighting its transformative potential, strengths, and vulnerabilities. It lays a valuable foundation for future research and discussions on the impact of the sharing economy on modern society and traditional business models.

Keywords

Sharing Economy, Airbnb, Logistic Regression Analysis, Property Blocking

Behavior, Peer-to-Peer Interactions

1. Introduction of Sharing Economy

The abstract delves into the transformative force of the sharing economy, exploring experiences like Airbnb and the unparalleled flexibility of Uber drivers. The subsequent comprehensive exploration delves into the core principles, advantages, and challenges of this innovative economic model, with a primary focus on the unique advantages offered by flexible work arrangements within the sharing economy, as evidenced by Uber drivers. The objective is to provide a thorough understanding of how this transformative phenomenon reshapes traditional notions of work and broader economic landscapes.

1.1. Understanding the Sharing Economy

The sharing economy, also known as collaborative consumption, represents a transformative shift in economic paradigms, diverging markedly from conventional business models. At its core, the sharing economy harnesses digital platforms to facilitate peer-to-peer interactions, enabling individuals to share resources, goods, and services directly with one another. This model prioritizes optimized resource utilization and fosters a sense of community by leveraging technology to create flexible work arrangements and innovative solutions to everyday needs. Embodying values of resource efficiency and sustainability, the sharing economy promotes a more equitable distribution of resources and encourages greater social and environmental responsibility.

1.2. The Value of Flexibility: Uber Drivers as a Case Study

The sharing economy's emphasis on flexibility is exemplified by Uber, revolutionizing the transportation sector. Uber drivers, in contrast to traditional employees, enjoy autonomy in determining work schedules and responding dynamically to unique circumstances. Chen et al. (2017) investigated the value of flexible work using Uber drivers, and the research "THE VALUE OF FLEXIBLE WORK: EVIDENCE FROM UBER DRIVERS," underscored the profound impact of flexible labor arrangements, allowing drivers to adapt their labor supply on an hourly basis, a departure from rigid conventional schedules.

1.3. Comparisons between Uber Drivers and Traditional Workers

A comparison between Uber drivers and traditional employees, using data from the American Time Use Survey (ATUS), reveals that traditional employment adheres predominantly to standard business hours. In contrast, Uber drivers exhibit a greater propensity to work during unconventional time slots, emphasizing the sharing economy's capacity to provide alternative labor opportunities beyond the 9-to-5 workday (Chen et al., 2017).

Within the Uber ecosystem, diverse driver profiles emerge, showcasing remarkable flexibility and strategic optimization of labor supply. Uber drivers can respond to demand fluctuations, such as surges in passenger requests, by evaluating reservation wages and potential income shocks, maximizing earnings in the sharing economy.

1.4. Challenges and Opportunities in the Sharing Economy

Despite its numerous advantages, the sharing economy presents a complex landscape of challenges and opportunities that require careful consideration. On one hand, questions surrounding labor rights, job security, income stability, data privacy, and platform access limitations underscore the need for robust regulatory frameworks and policy interventions to address emerging issues effectively (Chen et al., 2017). These challenges highlight the importance of safeguarding the rights and well-being of workers, ensuring fair and equitable participation, and mitigating risks associated with data privacy breaches and platform monopolies.

On the other hand, the sharing economy offers a range of opportunities for economic empowerment, innovation, and sustainability. Its emphasis on flexibility, autonomy, and collaboration enables individuals to access new income streams, pursue entrepreneurial ventures, and optimize resource utilization. Guo et al. (2020) explored the pricing strategies and decision preferences of sharing economy platforms, using DiDi as an example, proved that the sharing economy fosters innovation and creativity by providing a platform for diverse ideas and solutions to thrive (Guo et al., 2020). By promoting resource efficiency and environmental sustainability, it contributes to the transition towards a more sustainable and resilient economy.

In conclusion, while the sharing economy represents a paradigm shift in the way we work and consume, it requires careful navigation to maximize its benefits and mitigate its risks. Effective regulations and policies are essential to ensure fairness, equity, and accountability in the sharing economy, while also fostering innovation and economic growth. By striking a balance between regulation and innovation, policymakers can harness the full potential of the sharing economy to create a future where work and resources are optimized for the benefit of all participants.

2. Introduction of Airbnb

The shift in focus from Uber to Airbnb underscores the widespread influence of the sharing economy, revealing its transformative effects across various aspects of contemporary life beyond transportation. Similar to Uber, Airbnb showcases the dynamic interplay between innovative digital platforms and traditional industries, shaping economic paradigms.

In the sharing economy era, Airbnb stands as a significant platform that has redefined traditional hospitality, offering distinctive experiences and business opportunities. This exploration delves into the multifaceted impact of Airbnb on the market and society, providing insights into its operations, welfare implications, and relationship with conventional hotels. Additionally, it considers the potential future evolution of Airbnb while recognizing inherent weaknesses and potential threats.

2.1. Understanding Airbnb

Airbnb symbolizes the sharing economy—a digital marketplace connecting travelers with hosts willing to rent out their homes or spare rooms. Its unique features, including a flexible supply model, low entry barriers for hosts, and responsiveness to market dynamics, differentiate it from traditional accommodations, prompting questions about its potential impact on incumbent firms, particularly in the hotel industry.

2.2. Impacts on the Hotel Industry

Debates surround Airbnb's effect on traditional hotels, with studies suggesting an impact on hotel revenues. Byers et al. (2013) studied the impact of Airbnb on the hotel industry. Airbnb's strength lies in flexibility, enabling hosts to adjust prices and supply based on market conditions, affecting hotels' peak pricing power, although the impact varies across different hotel tiers (Byers et al., 2013).

2.3. Differential Impact on Incumbent Firms

Airbnb's influence on incumbent firms within the hotel industry varies based on price tiers, facilities, and brand strength. High-end hotels are more vulnerable, while those with business-related amenities remain competitive. Chain hotels, with established brands, are less affected, leaving independent, lower-tier hotels catering to non-business travelers most impacted (Byers et al., 2013).

2.4. Complementary Relationship with Hotels

Contrary to expectations of substitution, Airbnb and hotels often coexist in a complementary relationship. Farronato and Fradkin (2018) analyzed the welfare effects of peer entry in the accommodation market, with Airbnb as a case study. Airbnb tends to absorb high seasonal demand when hotels are fully booked, and cities with more Airbnb listings often see higher hotel revenues per available room (Farronato & Fradkin, 2018). Airbnb's personalized and niche offerings cater to travelers valuing distinctiveness over standardized hotel services.

2.5. Challenges and Inefficiencies

Despite its potential for disruption, Airbnb faces challenges related to limited reach and liquidity, which result in inefficiencies in matching supply and demand. Reach refers to the platform's penetration into various markets and its ability to attract both hosts and guests, while liquidity pertains to the ease with which hosts can convert their assets (i.e., available accommodations) into cash through bookings. Also, Cheng and Foley (2018) examined digital discrimination in the sharing economy, focusing on Airbnb. These challenges hinder Airbnb's competitiveness in the hospitality sector and contribute to its status as a secondary choice in cities with abundant hotel options (Cheng & Foley, 2018).

Additionally, the current state of peer-to-peer car rental markets reveals that only a fraction of the potential population is aware of their existence, and even fewer have actual access due to regulatory constraints. Fraiberger and Sundararajan (2015) studied peer-to-peer rental markets in the sharing economy. Counterfactual analyses predict significant changes in automobile ownership levels, with access to peer-to-peer marketplaces potentially leading to reductions in new and used car ownership and an increase in the proportion of the population opting not to own a car. While further empirical data is needed to fully interpret these results, even conservative estimates suggest a substantial shift towards non-ownership-based consumption for millions of people (Fraiberger & Sundararajan, 2015).

2.6. Welfare Implications

While disrupting the hospitality industry, Airbnb benefits consumers and society by increasing variety, exerting downward pressure on prices, and empowering below-median income consumers. Airbnb stimulates travel spending, benefiting local economies, and expands the overall travel market (Fraiberger & Sundararajan, 2015).

2.7. Conclusion

In conclusion, Airbnb exemplifies the transformative potential of the sharing economy, disrupting traditional accommodation notions and reshaping the competitive landscape of the hotel industry. While posing challenges to hotels, it also operates complementarity. The sharing economy, as exemplified by Airbnb, brings undeniable benefits to consumers and society. Its evolving nature raises questions about its future role, but its undeniable impact on the market and society continues to grow.

3. Introduction of Research of the Factors Influencing the Status of Airbnb Listings in New York in April, 2015

After delving into the background information surrounding Airbnb and its intricate relationship with the hospitality industry, it's time to delve into the core motivations driving this research. The primary aim of this study is to address a critical issue within the Airbnb ecosystem, the phenomenon of listing blocking. The central focus is to gain a comprehensive understanding of the diverse factors leading to listings being blocked, with a specific emphasis on those categorized under status B.

The global expansion of Airbnb over the last decade has undeniably transformed the hospitality landscape, presenting hosts and guests with a multitude of opportunities and challenges. Hosts benefit from the platform's ability to lower entry costs, allowing for increased participation in the sharing economy. However, challenges such as limited reach and liquidity can hinder hosts' ability to attract guests and generate income. Additionally, regulatory constraints in certain cities restrict the development of peer-to-peer rental markets, posing further obstacles for hosts.

For guests, Airbnb offers a diverse range of accommodation options and often provides a more personalized and unique experience compared to traditional hotels. The platform's flexibility allows guests to find accommodations that suit their preferences and budgets, contributing to a more customizable travel experience. However, awareness and accessibility issues may limit guests' options in certain locations, making Airbnb a secondary choice in cities with ample hotel options.

As the platform continues its growth, it becomes increasingly crucial to comprehend the determinants of Airbnb listing status, particularly those factors resulting in the status of "blocking."

Unraveling these determinants is significant due to the profound impact they have on both hosts and guests. For hosts, a blocked listing signifies not only a loss of potential revenue but also an inefficient allocation of resources. Conversely, for guests, blocked listings limit accommodation choices and impede the booking process, potentially diminishing their overall experience.

The driving force behind this research is firmly rooted in the desire to enhance the efficiency and profitability of Airbnb hosts while simultaneously improving the experience of Airbnb guests. This undertaking contributes to the overarching optimization of the Airbnb platform, making it more accessible, efficient, and accommodating for all stakeholders involved.

4. Data Analysis and Describution

With the overarching motivations clarified, the focus of our research now shifts to the critical phase of data analysis and description. This pivotal stage is supported by two primary datasets, "ny_april_10009_HAN (1) (1)" and "ny_property_HAN (1) (1)." The datasets, as the cornerstone of the research, offer a rich repository of diverse independent variables, each carrying the potential to exert influence on the status of individual Airbnb listings.

4.1. Dataset Analysis "ny4"

The research conducted in this study hinges on the comprehensive analysis of the dataset titled "ny_april_10009_HAN (1) (1)", hereafter referred to as "ny4." This dataset serves as a fundamental source of information pertaining to Airbnb listings in the dynamic city of New York during the month of April in the year 2015. "ny4" is a repository of diverse independent variables, each with the potential to exert influence on the status of individual Airbnb listings.

"ny4" encompasses a wealth of data, including crucial attributes such as property ID, sign-in dates, listing status, room prices, reservation IDs, year, and month. The dataset consists of a substantial sample size, totaling 30,090 observations.

The initial phase of analysis involves a thorough examination of various data types present in "ny4." Specifically, the study delves into the relationship between property ID and sign-in dates, revealing that each property is assigned a unique ID for each day of the month, encompassing the period from April 1, 2015, to April 30, 2015.

Regarding listing status, "ny4" classifies listings into three categories: A, B, and R. The analysis reveals that category A constitutes 13,853 listings (46% of the total), category B comprises 8948 listings (30%), and category R encompasses 7289 listings (24%).

When examining room prices, "ny4" unveils significant statistics. According to Figure 1 and Figure 2, the mean room price is $179.0765, with a median of $150. The dataset exhibits a variance of $16859.09, a standard deviation of $129.8426, a maximum price of $2500, and a minimum price of $40. A histogram illustrates that a majority of guests opt for rooms priced under $200, with a distinct preference for rates below $400.

Subsequently, the study scrutinizes the relationships between different data points within "ny4." Property ID, it is revealed, has a notable connection with room prices. A random sampling of five data subsets indicates that prices tend to remain constant for a given property ID, with occasional variations in some instances. This observation suggests that the price paid by guests may influence their assignment to specific property IDs.

However, as Figure 3 shows, an examination of the relationship between property ID and listing status does not reveal a significant correlation. Analysis tables demonstrate that the distribution of different listing statuses appears to be random across property IDs.

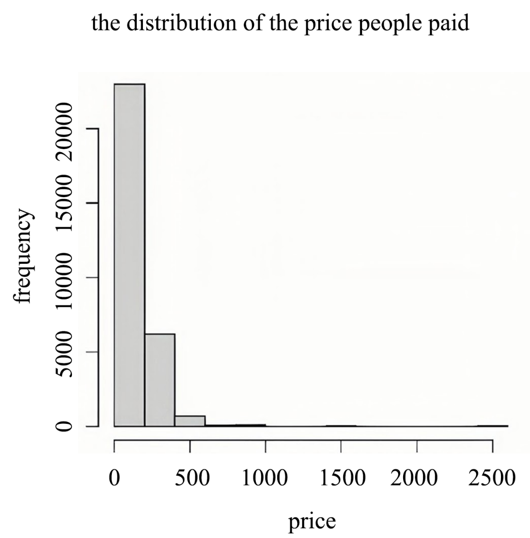

Figure 1. The distribution of price. Source: Elaborated by the authors.

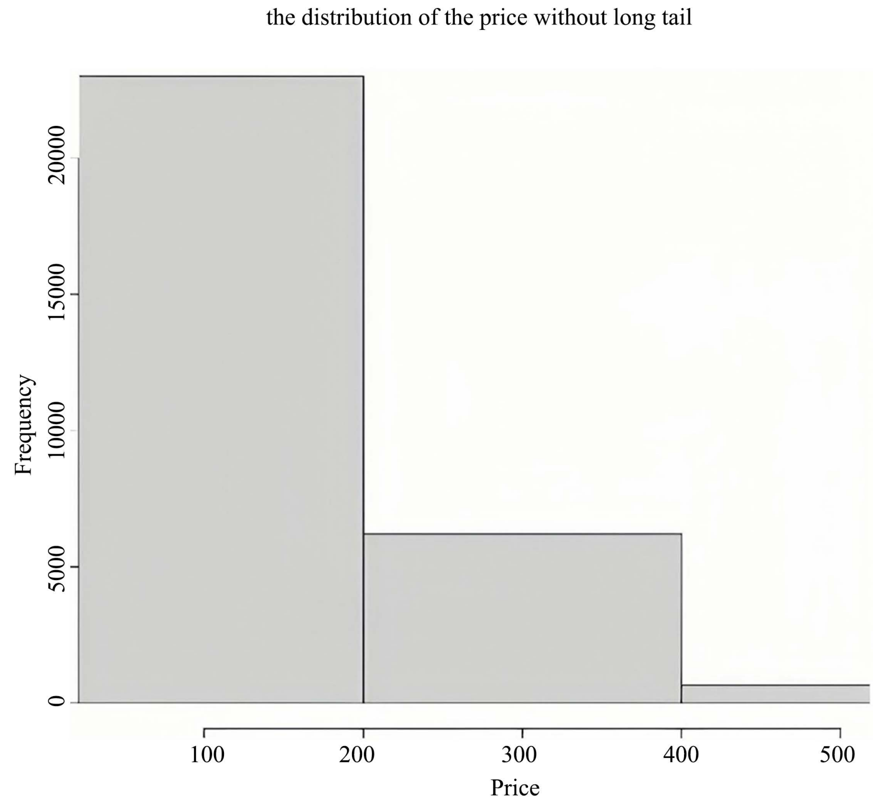

Figure 2. The distribution of price. Source: Elaborated by the authors.

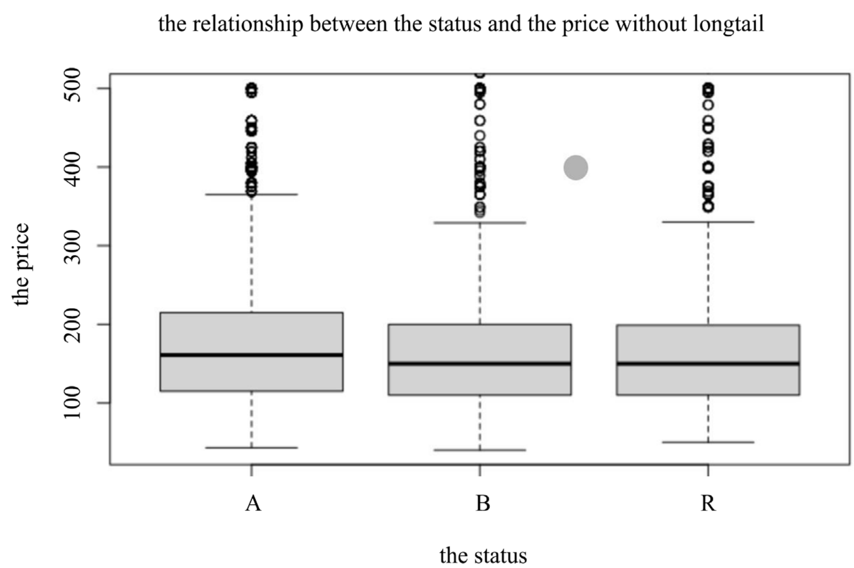

Figure 3. The relationship between status and price. Source: Elaborated by the authors.

Finally, the study explores the connection between listing status and room prices. Surprisingly, no clear relationship emerges between these variables. An analysis indicates that guests from listing statuses B and R often choose rooms with similar pricing, while guests from status A tend to select slightly higher-priced rooms.

In summary, "ny4" serves as the cornerstone of this research, offering a comprehensive view of Airbnb listings in New York City during April 2015. Through meticulous analysis, this dataset provides insights into the factors influencing listing status and offers valuable information on property IDs, listing statuses, and room prices. This analysis constitutes the foundation upon which the research's conclusions are built, contributing to a deeper understanding of Airbnb listing dynamics.

4.2. Dataset Analysis "nyp"

The dataset "nyp" offers a comprehensive view of Airbnb listings within New York City's 10,009 neighborhood. Comprising 2336 entries and spanning 49 distinct attributes, this dataset provides valuable insights into the characteristics of these listings.

In terms of location, these listings are concentrated within the 10,009 zip code area, specifically in the neighborhoods of East Village, NY-NJ-PA Metro Area, and Stuyvesant Town. Most listings cluster in a specific geographical region, indicative of their focus on the 10,009 zip code area.

These listings predominantly consist of apartments (98%) and are offered in various formats, including entire home/apartment (61%), private room (37%), and shared room (2%). Furthermore, the majority of these listings have one bedroom (70%), a single bathroom (90%), and can accommodate up to two guests (50%).

When it comes to service, listings maintain an average of fewer than 16 reviews. Superhosts, with a status of false (76%), true (5%), or other (19%), are also present in the dataset. The listings feature a range of cancellation policies, typically involving a security deposit between $200 and $500 and cleaning fees, which commonly amount to $50, $75, or $100.

Pricing varies across these listings, with an average daily rate of $206 and associated monthly and weekly rates. Additionally, data relating to annual revenue, occupancy rate, number of bookings, and reservation days over the last twelve months provides valuable insights into the growth potential of these listings.

The analysis of the "nyp" dataset focuses on the relationships between various attributes, from **Figure 4**, we focus on the particular attention to the interplay between pricing and ratings, utilizing the average daily rate as the pricing benchmark and the overall rating as the standard for evaluating guest satisfaction.

In this analysis shown in **Figure 5**, and the details are shown in **Figure 6** and **Figure 7**, neighborhood emerges as a key determinant of price and rating differences. Listings within the NY-NJ-PA Metro Area command higher prices compared to listings in other neighborhoods, though they tend to receive lower ratings due to their elevated costs. Regarding facilities, property types, such as townhouses, stand out with higher pricing, particularly among the upper 25% of such listings. In contrast, entire home/apartment and private room types tend to receive lower ratings.

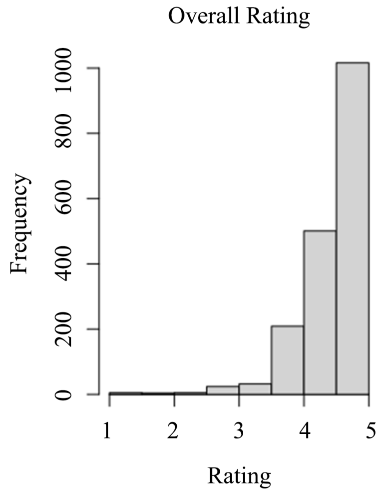

Figure 4. The distribution of rating. Source: Elaborated by the authors.

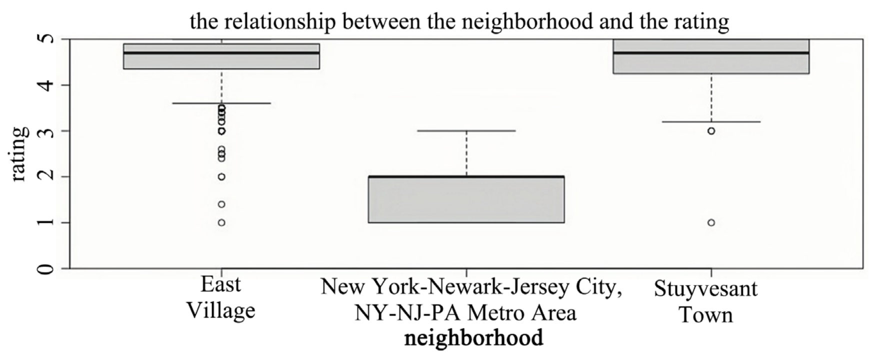

Figure 5. The relationship between neighborhood (Jersey City) and rating. Source: Elaborated by the authors.

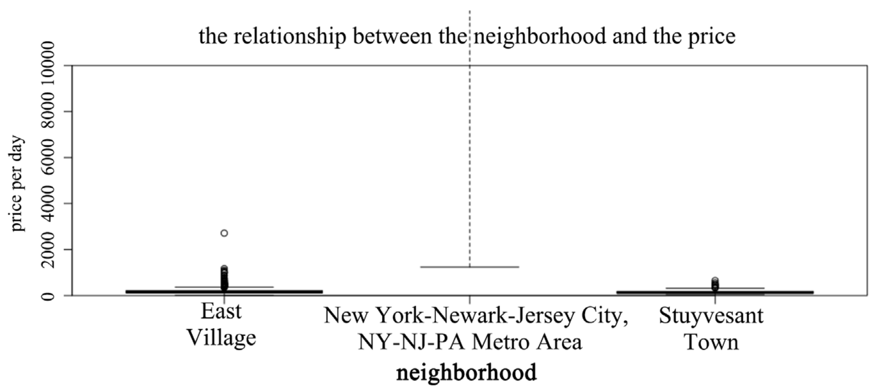

Figure 6. The relationship between neighborhood (Jersey City) and price per day. Source: Elaborated by the authors.

Bedroom and bathroom counts influence pricing, with higher numbers generally corresponding to higher prices. The maximum guest capacity also impacts pricing but has limited influence on ratings. The analysis also considers factors such as response rate, response time, superhost status, and cancellation policies, revealing that these do not significantly affect pricing or ratings.

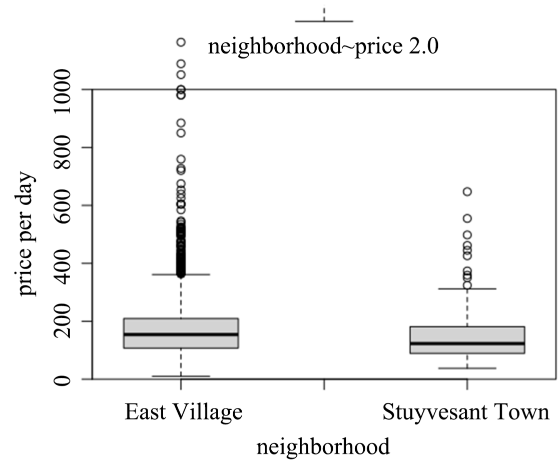

Figure 7. The relationship between neighborhood (East village and stuyvesant town) and price per day. Source: Elaborated by the authors.

In summary, the "nyp" dataset not only provides a comprehensive view of Airbnb listings in New York's 10,009 area but also offers insights into how various attributes are interconnected. This understanding can illuminate the factors affecting pricing and the guest experience within the Airbnb ecosystem.

5. Logistic Regression Analysis of Airbnb Status

After thoroughly analyzing the methodology and identifying significant predictors in the logistic regression model, let's shift our focus to the results generated by the regularization process. These results offer valuable insights into how the price influences the likelihood of Airbnb listings falling into different statuses. We examined the role of lambda values and intercepts, closely scrutinizing the direction and magnitude of the coefficients. The findings are thoroughly explained, providing insight into the complex dynamics that determine Airbnb listing status. This detailed exploration aims to facilitate an informed decision-making process aligned with the principles of rigorous data analysis and research.

5.1. Introduction

In this comprehensive data report, we delve into the intricate landscape of Airbnb listings, with a specific focus on the key factors influencing their status. Utilizing logistic regression models, our goal is to uncover what distinguishes Airbnb listings labeled as "B" status, setting them apart from "A" or "R" statuses. The dataset under examination is the meticulously curated nyp4.5, a cleaned and merged version of two datasets: "ny_april_10009_HAN (1) (1)" and "ny_property_HAN (1) (1)."

The crux of this analysis lies in defining the dependent variables: assigning "B" as 1, while "A" and "R" are labeled as 0. The objective is to unveil the factors that significantly influence an Airbnb listing being designated as "B" status, particularly when compared to other statuses.

The nyp4.5 dataset serves as a comprehensive repository, encompassing various key attributes that vividly portray Airbnb listings in New York in April 2015. It includes numerous independent variables such as "price," "property type," "listing type," "neighborhood," "average daily rate," "number of bookings in the past 12 months," "cleaning fee," "per nightly release rates," and more. Rest assured, this dataset has undergone a rigorous cleaning process to ensure data integrity and completeness, with careful handling of missing values.

Through the lens of logistic regression, we embark on a journey to uncover the underlying factors that elevate certain Airbnb listings to "B" status, providing insights into the dynamics governing the Airbnb ecosystem.

5.2. Methodology

A logistic regression model was employed to estimate the relationship between the dependent variable (B = 1, and A, R = 0) and the independent variables. Bock (2022) provided guidance on interpreting logistic regression coefficients. The logistic regression model is well-suited for analyzing binary outcomes, making it an appropriate choice for predicting the probability of an Airbnb listing being in status "B."

5.3. Model Estimation Results

Variables	Coefficient	Std.Error	Z-statisics	*p*-value	Significant Code
(Intercept)	2.29 × 10^3	1.06 × 10^3	2.15 × 10^0	3.12 × 10^−2	*
Price	−9.76 × 10^−3	8.42 × 10^−4	−1.16 × 10^1	2 × 10^−16	***
Property Type - Bed & Breakfast	6.70 × 10^0	7.54 × 10^−1	8.89 × 10^0	2 × 10^−16	***
Property Type - Cabin	−1.32 × 10^1	2.65 × 10^2	−5.00 × 10^−2	9.60 × 10^−1	
Property Type - Condominium	−1.97 × 10^0	3.53 × 10^−1	−5.59 × 10^0	2.32 × 10^−8	***
Property Type - House	−1.73 × 10^0	7.42 × 10^−1	−2.34 × 10^0	1.96 × 10^−2	*
Property Type - Loft	−1.04 × 10^1	2.66 × 10^2	−3.90 × 10^−2	9.69 × 10^−1	
Property Type - Townhouse	−1.38 × 10^1	2.66 × 10^2	−5.20 × 10^−2	9.59 × 10^−1	
Listing Type - Private room	−7.27 × 10^−1	8.15 × 10^−2	−8.92 × 10^0	2 × 10^−16	***
Listing Type - Shared room	−8.80 × 10^−1	5.30 × 10^−1	−1.66 × 10^0	9.67 × 10^−2	
Neighborhood - Stuyvesant Town	−9.90 × 10^−1	2.36 × 10^−1	−4.19 × 10^0	2.78 × 10^−5	***
Average Daily Rate	8.71 × 10^−3	1.12 × 10^−3	7.75 × 10^0	9.35 × 10^−15	***
Annual Revenue LTM	1.29 × 10^−6	2.91 × 10^−6	4.43 × 10^−1	6.57 × 10^−1	
Occupancy Rate LTM	−4.61 × 10^−1	2.38 × 10^−1	−1.94 × 10^0	5.23 × 10^−2	
Number of Bookings LTM	−1.23 × 10^−2	3.76 × 10^−3	−3.28 × 10^0	1.04 × 10^−3	**
Number of Reviews	−4.59 × 10^−4	1.39 × 10^−3	−3.31 × 10^−1	7.41 × 10^−1	
Overall Rating	4.59 × 10^−1	9.98 × 10^−2	4.60 × 10^0	4.15 × 10^−6	***
Bedrooms	1.01 × 10^−1	6.14 × 10^−2	1.65 × 10^0	10.00 × 10^−2	

Continued

Bathrooms	8.00×10^{-1}	1.14×10^{-1}	7.05×10^{0}	1.83×10^{-12}	***
Max Guests	-1.77×10^{-1}	2.93×10^{-2}	-6.06×10^{0}	1.38×10^{-9}	***
Response Rate	8.78×10^{-3}	2.45×10^{-3}	3.58×10^{0}	3.43×10^{-4}	***
Response Time (min)	6.57×10^{-4}	1.19×10^{-2}	5.52×10^{0}	3.32×10^{-8}	***
Superhost - NA	-8.32×10^{-1}	2.87×10^{-1}	-2.90×10^{0}	3.76×10^{-3}	**
Superhost - TRUE	1.42×10^{-1}	9.64×10^{-2}	1.48×10^{0}	1.40×10^{-1}	
Cancellation Policy - Moderate	3.33×10^{-1}	1.28×10^{-1}	2.59×10^{0}	9.48×10^{-3}	**
Cancellation Policy - Strict	9.24×10^{-1}	1.21×10^{-1}	7.62×10^{0}	2.61×10^{-14}	***
Security Deposit	2.83×10^{-5}	7.84×10^{-5}	3.60×10^{-1}	7.19×10^{-1}	
Cleaning Fee	-1.92×10^{-2}	1.25×10^{-3}	-1.53×10^{1}	2×10^{-16}	***
Extra People Fee	-8.55×10^{-3}	1.05×10^{-3}	-8.11×10^{0}	4.89×10^{-16}	***
Published Nightly Rate	8.40×10^{-3}	8.89×10^{-4}	9.46×10^{0}	2×10^{-16}	***
Published Monthly Rate	-5.58×10^{-6}	3.10×10^{-5}	-1.80×10^{-1}	8.57×10^{-1}	
Published Weekly Rate	-9.25×10^{-4}	1.44×10^{-4}	-6.43×10^{0}	1.27×10^{-10}	***
Minimum Stay	1.30×10^{-2}	6.78×10^{-3}	1.91×10^{0}	5.56×10^{-2}	
Count Reservation Days LTM	-3.44×10^{-3}	1.15×10^{-3}	-2.98×10^{0}	2.89×10^{-3}	**
Count Available Days LTM	-7.80×10^{-3}	8.53×10^{-4}	-9.14×10^{0}	2×10^{-16}	***
Count Blocked Days LTM	3.99×10^{-3}	6.43×10^{-4}	6.21×10^{0}	5.49×10^{-10}	***
Number of Photos	-1.31×10^{-2}	2.76×10^{-3}	-4.74×10^{0}	2.13×10^{-6}	***
Business Ready - TRUE	3.04×10^{-1}	1.06×10^{-1}	2.86×10^{0}	4.25×10^{-3}	**
Instantbook Enabled - Yes	-1.01×10^{0}	1.25×10^{-1}	-8.11×10^{0}	5.20×10^{-16}	***
Latitude	4.81×10^{1}	1.21×10^{1}	3.99×10^{0}	6.49×10^{-5}	***
Longitude	5.75×10^{1}	1.24×10^{1}	4.64×10^{0}	3.52×10^{9}	***

5.4. Interpretation of the Results

The logistic regression model's results reveal several significant predictors. Variables with positive coefficients have a higher likelihood of being in status "B" compared to "A" or "R," while variables with negative coefficients are less likely to be in the status of "B" than "A" or "R." Larger coefficient values indicate a stronger impact on the outcome probability. Additionally, the significance of each coefficient is determined by its associated *p*-value, where variables with *p*-values less than the chosen significance level (often 0.05) are considered statistically significant, indicating a significant impact on the outcome.

The analysis highlights notable relationships between predictor variables and the likelihood of an Airbnb listing being in status "B." For instance, the "Price" variable exhibits a strong negative relationship, indicating that as the price of an Airbnb listing increases, the likelihood of it being in status "B" decreases significantly (p-value < 2e−16). Similarly, listings categorized as "Condominium" or "House" have lower odds of being in status "B" compared to statuses "A" or "R." Additionally, higher cleaning fees, higher published weekly rates, and a higher number of shared photos are associated with a lower likelihood of the listings being in status "B".

On the contrary, listings with higher average daily rates, higher "Extra People Fee" costs, higher booking volume, higher overall ratings, more bathrooms, higher maximum guest capacity, higher response rates, shorter response times, or higher published nightly rates have a higher possibility of being in status "B" than in "A" or "R". Moreover, listings with a "Private room" type, categorized as "Bed & Breakfast," or located in the "Stuyvesant Town" neighborhood are more likely to be in the status of "B" compared to "A" or "R".

An interesting observation from this result is that both listings with a higher count of available days and listings with a higher count of blocked days are associated with a higher likelihood of the listing being in status "B." This suggests that the decision of homeowners to block their Airbnb is not significantly affected by their past actions.

Overall, the logistic regression model provides valuable insights into the factors influencing the likelihood of Airbnb listings being in status "B" versus statuses "A" or "R". These findings can guide decision-making and inform strategies for optimizing listing status and potential revenue.

5.5. Model Fit and Goodness-of-Fit

The logistic regression model's goodness-of-fit was assessed using the null deviance and residual deviance. HanzyHanzy and Li (1965) discussed logistic regression intercept adjusting average fitted probabilities. The null deviance, which is 11476.5, represents the deviance of a model with no predictors. The residual deviance, on the other hand, is 8066.1, indicating the deviance after fitting the logistic regression model.

The AIC value of the model is 8148.1, which is used to compare different models. Lower AIC values imply better model fit and parsimony.

5.6. Regularization Results

Variables	Results
Intercept	2.37 × 10^3
Price	−9.45 × 10^−3
Property Type - Bed & Breakfast	6.62 × 10^0
Property Type - Cabin	−3.82 × 10^0
Property Type - Condominium	−1.94 × 10^0
Property Type - House	−1.67 × 10^0
Property Type - Loft	−1.07 × 10^0

Continued

Property Type - Townhouse	−4.23 × 10^0
Listing Type - Private room	−7.21 × 10^−1
Listing Type - Shared room	−8.47 × 10^−1
Neighborhood - Stuyvesant Town	−9.68 × 10^−1
Average Daily Rate	8.29 × 10^−3
Annual Revenue LTM (Last Twelve Months)	1.26 × 10^−6
Occupancy Rate LTM (Last Twelve Months)	−4.47 × 10^−1
Number of Bookings LTM (Last Twelve Months)	−1.19 × 10^−2
Number of Reviews	−4.08 × 10^−4
Overall Rating	4.67 × 10^−1
Bedrooms	9.82 × 10^−2
Bathrooms	7.87 × 10^−1
Max Guests	−1.74 × 10^−1
Response Rate	8.49 × 10^−3
Response Time (min)	6.48 × 10^−4
Superhost - NA (Not Available)	−8.20 × 10^−1
Superhost - TRUE	1.34 × 10^−1
Cancellation Policy - Moderate	3.18 × 10^−1
Cancellation Policy - Strict	9.04 × 10^−1
Security Deposit	2.69 × 10^−5
Cleaning Fee	−1.85 × 10^−2
Extra People Fee	−8.37 × 10^−3
Published Nightly Rate	8.02 × 10^−3
Published Monthly Rate	−4.30 × 10^−8
Published Weekly Rate	−8.75 × 10^−4
Minimum Stay	1.29 × 10^−2
Count Reservation Days LTM (Last Twelve Months)	−3.42 × 10^−3
Count Available Days LTM (Last Twelve Months)	−7.64 × 10^−3
Count Blocked Days LTM (Last Twelve Months)	4.08 × 10^−3
Number of Photos	−1.28 × 10^−2
Business Ready - TRUE	2.90 × 10^−1
Instantbook Enabled - Yes	−1.01 × 10^0
Latitude	4.58 × 10^1
Longtitude	5.72 × 10^1

5.7. Regularization Interpretation

The regularization results provide valuable insights into how price affects the likelihood of an Airbnb being in different statuses.

The lambda value of this model is low, (0.00015), which means that the regularization penalty is relatively weak.

An intercept of 2.3678e+03 represents the Airbnbs are in the status of "A" or "R" when all predictor variables are at zero.

Coming to the coefficient, the coefficients indicate the direction and magnitude of the effect of each predictor on the likelihood of the outcome being in class "B" compared to the reference category (usually class "A" or "R"). The positive coefficients indicate that an increase in the predictor variable leads to a higher likelihood of being in status "B," while negative coefficients suggest the opposite. The magnitude of each coefficient represents the strength of the relationship.

5.8. Conclusion

The logistic regression analysis provides valuable insights into the factors influencing the status of Airbnb listings. Notably, "Price" emerges as a significant predictor, with higher prices leading to a reduced likelihood of an Airbnb being in status "B." Additionally, various "Property Type," "Listing Type," and other features demonstrate their influence on the dependent variable.

The logistic regression model fits the data reasonably well, as evidenced by the goodness-of-fit statistics. However, it is essential to acknowledge potential limitations and sources of bias in the analysis.

6. Logistic Regression Analysis of Price and Airbnb Status

With a detailed analysis of the results from our logistic regression model, the focus now shifts to the regularization results, providing further insights into the impact of price on the status of Airbnb listings. These regularization results shed light on the strength of the relationship between price and Airbnb statuses, offering a more nuanced perspective on the role of price as a determinant.

6.1. Introduction

This data report delves into a detailed logistic regression analysis, which zeroes in on the relationship between the price of Airbnb listings and their corresponding status. The primary objective of this study is to ascertain whether the price stands as a significant determinant of the status of Airbnb listings, with a particular emphasis on the "B" status as opposed to the "A" and "R" statuses.

The dataset under scrutiny, "ny4," encapsulates a wealth of information concerning Airbnb listings in New York during April 2015. This dataset comprises an array of independent variables that have the potential to exert influence over the status assigned to each listing. However, for the purpose of this logistic regression analysis, our focal point is a single key variable: "Price." This variable specifically denotes the nightly rate charged to guests for their stay, a pivotal factor in the context of Airbnb status.

6.2. Methodology

The analysis utilized logistic regression to model the relationship between the binary dependent variable "Status B" (coded as 0) and the independent variable "Price." The dataset consisted of Airbnb listings, and we examined how changes in the price impact the likelihood of listings falling into status B compared to statuses A and R.

6.3. Results

Variables	Coefficient	Std. Error	Z-Statistics	*p*-value
Intercept	−8.743e−01	2.131e−02	−41.026	<2e−16 ***
Price	8.067e−05	9.564e−05	0.843	0.399

Null deviance: 36627 on 30089 degrees of freedom. Residual deviance: 36626 on 30088 degrees of freedom.

6.4. Model Estimation Results

The intercept in the model is −0.8743 with a standard error of 0.0213. It indicates the expected log-odds of status B when the price of Airbnb is zero.

The coefficient for the variable "Price" is 0.00008067 with a standard error of 0.00009564. This coefficient represents the change in the log-odds of being in status B for each one-unit increase in the price of Airbnb.

However, the *p*-value for the "Price" variable is 0.399, which is greater than the significance level (usually 0.05). It suggests that the relationship between the price and status B is not statistically significant at the 5% level.

6.5. Model Fit and Goodness-of-Fit

The model's fit can be assessed by comparing the Null deviance and Residual deviance. The Null deviance represents the deviance of a model with only an intercept (no predictors), while the Residual deviance is the deviance of the fitted model. In this case, the Null deviance was 36,627, and the Residual deviance was 36,626. Since both values are very close, it indicates that the model doesn't significantly improve upon the null model, suggesting a weak relationship between price and status B.

6.6. Regularization Results

Best Lambda	0.001532
Coefficient	−8.643712e−01
Intercept	2.5337973e−05

6.7. Regularization Interpretation

The regularization results provide valuable insights into how price affects the likelihood of an Airbnb being in different statuses.

A low lambda value (0.0015) indicates a relatively weak regularization penalty, which allowed the model to have larger coefficients.

The coefficient of price is −8.643712e−01, with an odds ratio less than 1 (0.42). This suggests that as the price increases, the likelihood of an Airbnb being in status "B" decreases.

The intercept value is approximately 2.5337973e−05 (close to 0), and the odds intercept is 1. This implies that if the price is 0, the status of the Airbnb has to be in status "B" compared to the other two statuses.

6.8. Conclusion

Based on the logistic regression results, there is no statistically significant relationship between the price of the Airbnb and status B (when compared to statuses A and R). The coefficient for the "Price" variable is not significantly different from zero, meaning that the price does not appear to be a strong predictor of status B.

It's important to interpret these results with caution and consider other factors that may influence the status of an Airbnb listing.

7. Analysis of Property Blocking Behavior and Supply Curve Dynamics

Having unveiled pivotal insights into the ramifications of blocking behavior and supply curve dynamics on property revenues and occupancy rates, a comprehensive interpretation of these findings is conducted. The subsequent section will meticulously expound upon the results, exploring the observed trends and their implications for property management strategies.

7.1. Introduction

With the logistic regression analysis having effectively revealed the predictive potential of property blocking status, the focus of this investigation now shifts towards delving deeper into the blocking behavior exhibited by property owners and its intricate relationship with the dynamics of the supply curve. This research offers a comprehensive understanding of how property owners' choices to block their properties exert influence on revenue and occupancy rates. By engaging in a thorough exploration of the factors contributing to the blocking phenomenon, this study seeks to uncover the underlying patterns that can provide valuable insights for refining property management strategies.

7.2. Methodology

The research approach employed a systematic combination of data analysis, data visualization, and statistical modeling techniques. This comprehensive methodology encompassed various essential steps.

Firstly, the dataset amalgamation, which included "ny_april_10009_HAN_1_1_2," "ny_property_HAN (1) (1) 2," and "nyd_sta," underwent meticulous preprocessing to ensure the precision and relevance of the data. Notable transformations were introduced, such as the derivation of the "FractionSupplied" metric, calculated as (TotalDays - BlockedDays)/TotalDays, offering insight into the proportion of days each property was available for booking. Additionally, data organization was conducted based on PropertyID, ensuring that each property was represented by a singular data row. The property status was replaced with "BlockingStatus," reflecting the average blocking behavior over a given month. Moreover, properties were thoughtfully grouped by their respective neighborhoods, East Village and Stuyvesant Town, facilitating an in-depth analysis of neighborhood-specific trends. This rigorous data preprocessing was integral for subsequent analytical insights.

Next, model selection and linear regression are done to quantify relationships between key variables. The chosen model featured daily revenue as the dependent variable (y) and the fraction of days supplied as the independent variable (x). This selection was driven by the hypothesis that the willingness to block properties is linked to supply dynamics.

In addition, data visualization techniques were employed, which included scatter plots and line plots to visually represent supply curve dynamics and property attributes about blocking behavior. The process began by confirming the impact of daily revenue and booking volume on blocking. This was achieved through the plotting of daily revenue, which reflected the willingness to block, against the fraction of days supplied. These visualizations provided insights into how the inclination to block listings changes as the supply of available booking days fluctuates, shedding light on the supply and demand equilibrium. Further granularity was achieved by creating separate graphs for each neighborhood, allowing for a comparative analysis of the supply curves of properties within the same neighborhood but of different types and sizes. This approach revealed potential variations in blocking behavior among properties sharing a common neighborhood but possessing diverse characteristics.

7.3. Results and Analysis

7.3.1. Supply Curve Analysis

There is a noticeable trend where properties with higher average daily rates tend to have a higher likelihood of being blocked. As the fraction of days supplied increases, properties with higher rates shift towards being more frequently blocked (indicated by the transition from blue to red). The transition from blue to red also suggests this finding.

According to **Figure 8**, the relationship between higher average daily rates and increased blocking frequency suggests that property owners adopt a blocking strategy in response to certain demand thresholds, which could be a level of demand at which blocking their units becomes advantageous for revenue optimization.

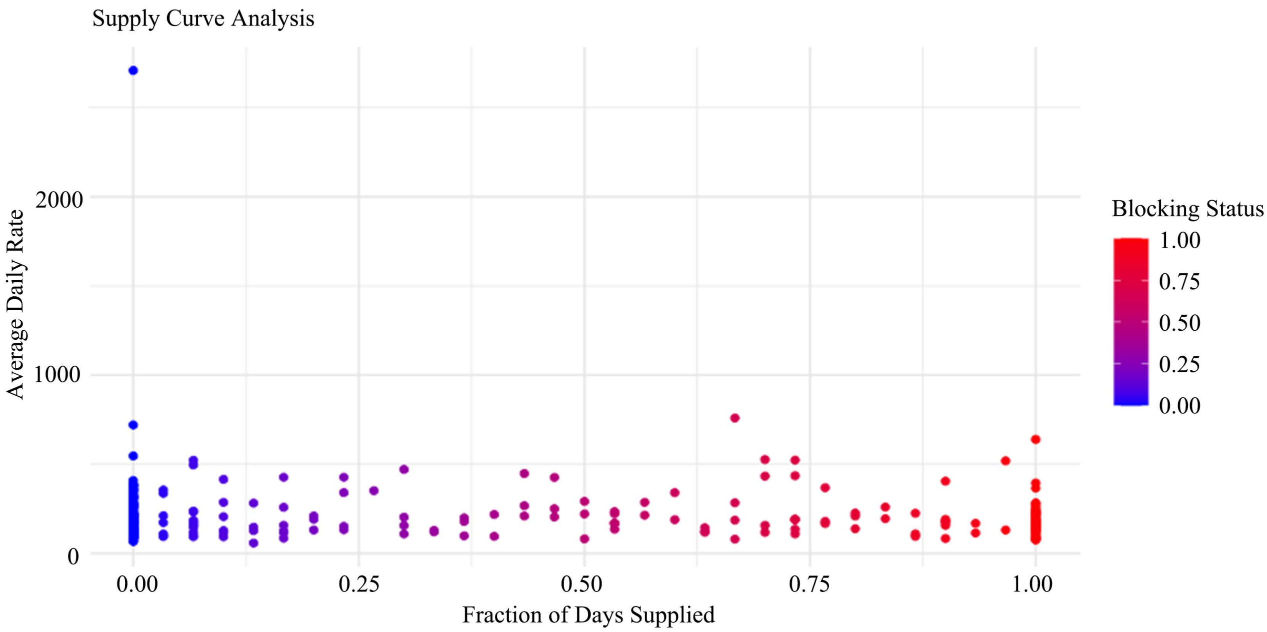

Figure 8. The relationship between day supplied and daily rate. Source: Elaborated by the authors.

When the average daily rate is higher, property owners might be more confident in temporarily blocking their listings to create scarcity and potentially secure higher rates during periods of peak demand. This strategic blocking approach aligns with revenue maximization strategies, enabling property owners to capitalize on higher-demand periods without sacrificing overall revenue.

7.3.2. East Village Neighborhood Analysis

In the examination of Property Type and Revenue, shown in **Figure 9**, it was apparent that the majority of properties within the dataset fell under the category of apartments. These apartments typically maintained average daily revenues that were below the $750 mark. This data underscored a prevalent preference for apartments among property owners, with most listings catering to guests seeking more budget-conscious options.

As for the Supply-Demand Balance, an intriguing trend emerged. It was observed that as the fraction of days supplied increased, there was a notable decrease in the number of data points. These data points were primarily clustered within the range of 0 to 1 day supplies. This phenomenon implied that property owners in this neighborhood exhibited a growing selectiveness as the supply approached full capacity. The indication was that property owners deliberately blocked certain dates, potentially creating a sense of scarcity and heightened demand for their listings during specific periods. This strategic behavior aligns with revenue optimization strategies, allowing property owners to leverage peak demand without compromising their overall revenue.

7.3.3. Stuyvesant Town Neighborhood Analysis

Upon closer observation of the Stuyvesant Town neighborhood, it was evident in **Figure 10** that this locale was predominantly characterized by apartments, with

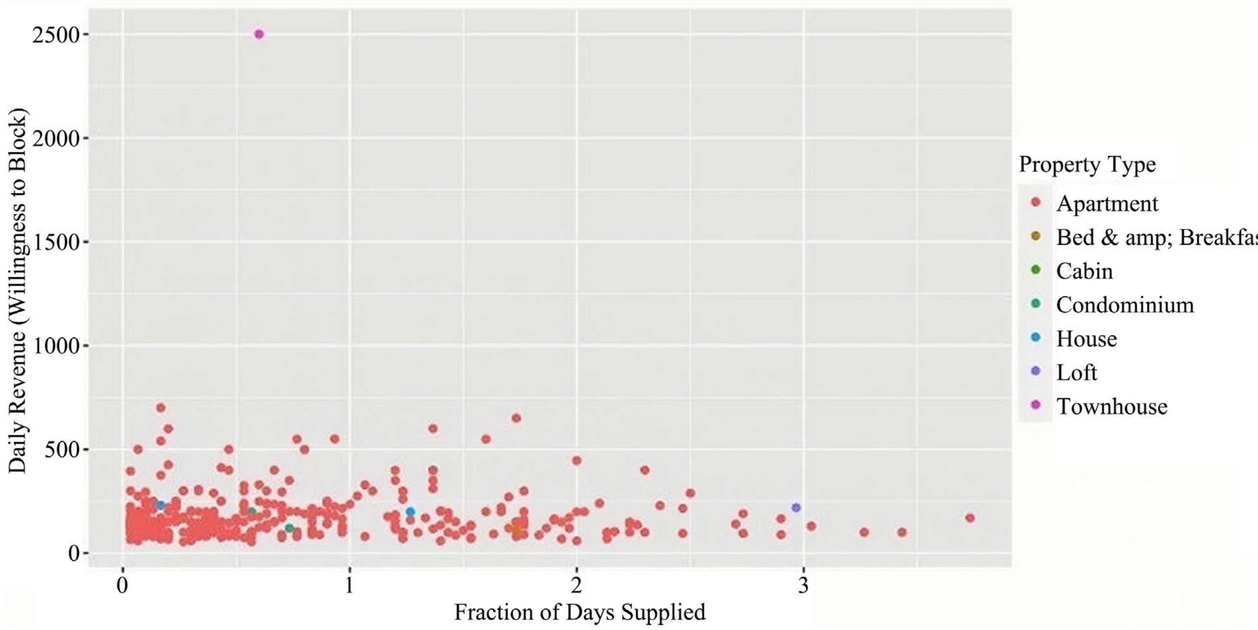

Figure 9. The relationship between day supplied and daily revenue for different property types. Source: Elaborated by the authors.

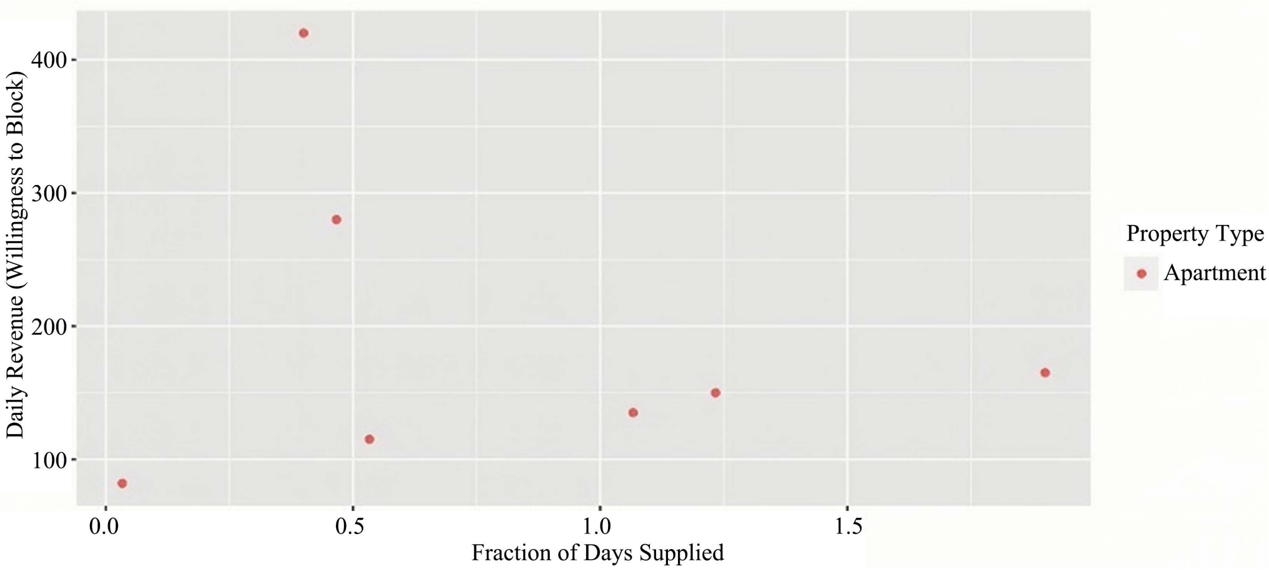

Figure 10. The relationship between day supplied and daily revenue of apartment listings. Source: Elaborated by the authors.

the average daily revenues typically remaining below the $200 threshold. This data indicated a distinct pricing structure in Stuyvesant Town, setting it apart from the East Village.

In terms of Supply-Demand Balance, the dataset for Stuyvesant Town presented a contrasting pattern. It featured a smaller number of properties, and all of these properties belonged to the "Apartment" category. Unlike the East Village, where property characteristics exhibited more defined trends, the properties in Stuyvesant Town displayed a more randomized distribution across a range of average daily rates. This variance highlighted a lack of consistent and discernible strategies in terms of the days supplied in the Stuyvesant Town neighborhood. It appears that property owners in this area did not adhere to a uniform blocking pattern, possibly reflecting the dynamic and less standardized nature of their offerings.

8. Supplementary Analysis

This study delves into the connection between property blocking patterns and annual revenue in the Airbnb space. It illuminates the complex dynamics that shape the Airbnb ecosystem, providing insights into understanding host behavior and property performance.

8.1. Introduction

The paper conducts a detailed analysis of the relationship between property-blocking behavior in Airbnb listings and annual income. Using classification criteria calculated by median price and average blocking rate, the study divided the listings into two clear groups. The first group includes listings with higher average prices and blocking rates, while the second group includes listings with lower average prices and blocking rates. The main objective is to evaluate the impact of price-related factors on the likelihood that a listing belongs to group 1 or 2, and how these classifications affect annual revenue.

8.2. Analysis for Different Factors

8.2.1. Price

The analysis focuses on the relationship between blocking behavior and annual revenue. The median price and average blocking rate are calculated, and the listings are separated into two groups:

- Group 1: Listings with a higher average price and higher blocking rate.
- Group 2: Listings with a lower average price and lower blocking rate.

A t-test to compare the annual revenue between the two groups is performed, with the null hypothesis being that there is no significant difference in revenue between the groups.

Results Interpretation:

- Among 306 listings, there are 58% (179) properties in group 1 that have higher rates and more frequent blocks, and 42% (127) properties in group 2 that have lower rates and fewer blocks.
- The t-test results indicated a statistically significant difference in annual revenue between the two groups.
- Group 1 (higher rate, higher blocking) had a higher mean annual revenue of $33215.20 compared to Group 2 (lower rate, lower blocking) with a mean annual revenue of $16204.18.

The result suggests a strong relationship between blocking behavior and annual revenue for Airbnb listings. Listings that charge higher rates and block more often tend to generate higher revenue.

Analysis:

According to the logical regression results, higher annual revenue rates are associated with a higher likelihood of "Status B." This positive impact indicates that an increased average revenue is linked to a higher probability of "Status B" occurring. This could be because higher revenue and rates might indicate a higher level of demand or popularity for the property. As a result, owners may be more inclined to block certain dates to ensure they can maximize their profits during peak periods. Furthermore, from this analysis, listings that block more often can also generate higher revenue by charging more.

8.2.2. Property

The primary objective of this analysis is to examine the relationship between various property characteristics and the likelihood of a listing being blocked on a given day.

A logistic regression model was constructed to investigate the relationship between property types and blocking behavior. The results revealed a statistically significant relationship (p-value < 0.001). The likelihood ratio test demonstrated that including property types as predictors improved the model fit.

Results Interpretation:

The coefficients for each property type provide insights into how different property types impact the likelihood of being blocked:

- Bed & Breakfast: Having a significantly higher likelihood of being blocked compared to other property types (Estimate: 3.376, p-value < 0.001).
- Condominium: having a slightly lower likelihood of being blocked (Estimate: −0.757, p-value = 0.024).
- House: It is also less likely to be blocked (Estimate: −3.341, p-value < 0.001).
- Cabin, Loft, Townhouse: These property types do not exhibit significant associations with blocking behavior.

According to **Figure 11**, the result suggests that listings categorized as "Bed & Breakfast" are more likely to be blocked, possibly due to unique operational and booking patterns associated with this type. Conversely, properties classified as "House" or "Condominium" are less likely to be blocked, reflecting a different set of guest expectations or management practices.

Analysis:

The level of competition in the market may affect the property's status. B & B owners may be more inclined to block specific dates during peak seasons or events to secure bookings, resulting in a higher likelihood of "B" occurring. On the other hand, in a competitive market, owners of cottages, apartments, houses, lofts, and townhouses may prefer to be flexible with availability, thereby reducing the likelihood of "B" occurring.

The size of a property can influence how well it attracts different types of guests. Larger properties, such as cottages, houses, and townhouses, may be better suited for families or groups, making them more popular for longer stays. Owners of such properties may prefer to accept bookings year-round, which

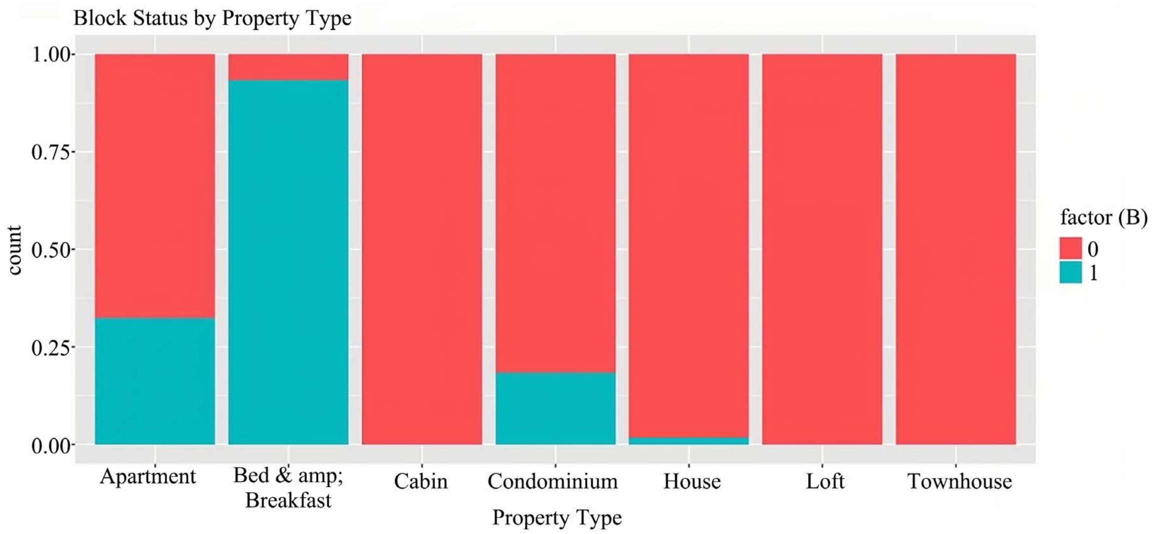

Figure 11. The effect of property types on blocking status. Source: Elaborated by the authors. * "1" represents a blocked day, while "0" indicates an unblocked day.

may result in a lower probability of "B". On the other hand, smaller properties like B & Bs and lofts may be more popular with couples or solo travelers, leading to a more selective booking cycle and a higher likelihood of "B" occurring. Furthermore, this type of accommodation is often associated with unique and personalized experiences, and B & B owners have greater flexibility in adjusting availability, further influencing the observed relationships.

8.2.3. Different Fee

The analysis put emphasis on how different types of extra fees would have different impact on the blocking.

- Security Deposit:

The logical regression results in **Figure 12** also suggest that listings with a security deposit are associated with a decreased likelihood of being blocked.

- Cleaning Fee:

Similar to the security deposit, as shown in **Figure 13**, listings with a cleaning fee are associated with a decreased likelihood of being blocked, as indicated by the negative coefficient and significant *p*-value.

- Extra People Fee:

According to the logical regression model in **Figure 14**, the presence of an extra people fee does not have a clear association with the likelihood of being blocked. However, the coefficient is not interpretable due to the singularity issue, and this should be further investigated or addressed.

- All Extra Fee:

Therefore, the presence of security deposits and cleaning fees seems to impact whether a listing is blocked, but the effect of an additional fee for extra people on blocking status is inconclusive based on the available data, as shown in **Figure 15**. Consequently, there is no clear correlation between any additional fee and the likelihood of being blocked.

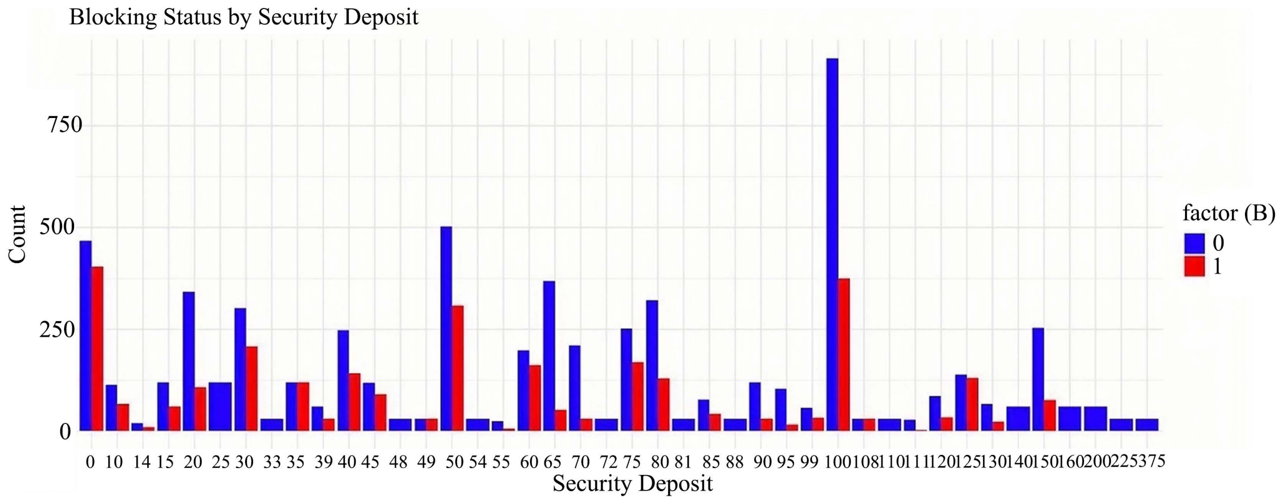

Figure 12. The effect of security deposit on blocking status. Source: Elaborated by the authors.

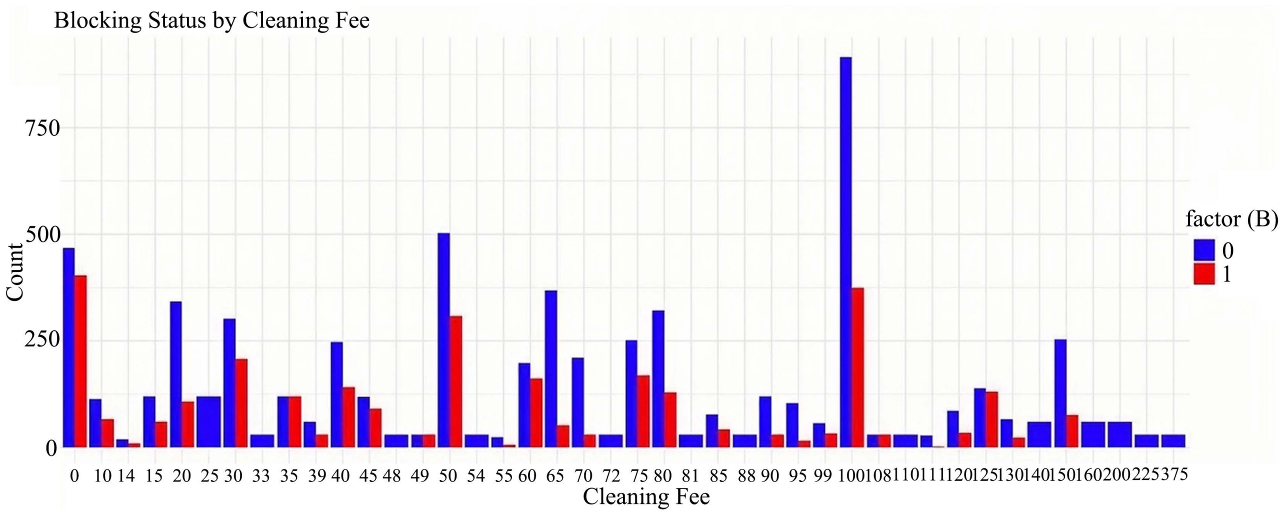

Figure 13. The effect of cleaning fee on blocking status. Source: Elaborated by the authors.

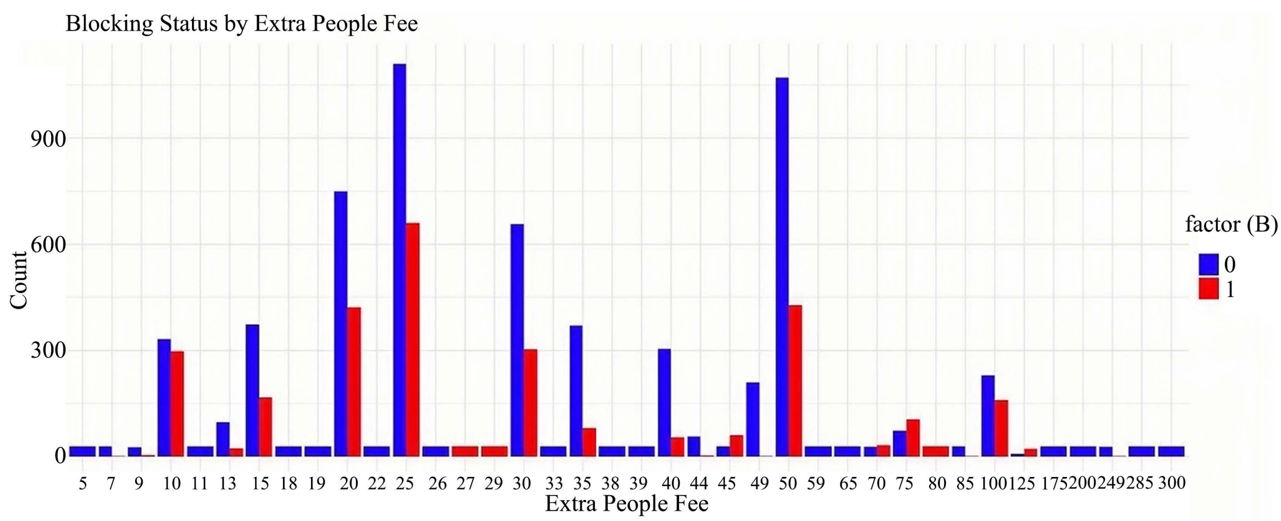

Figure 14. The effect of extra people fee on blocking status. Source: Elaborated by the authors.

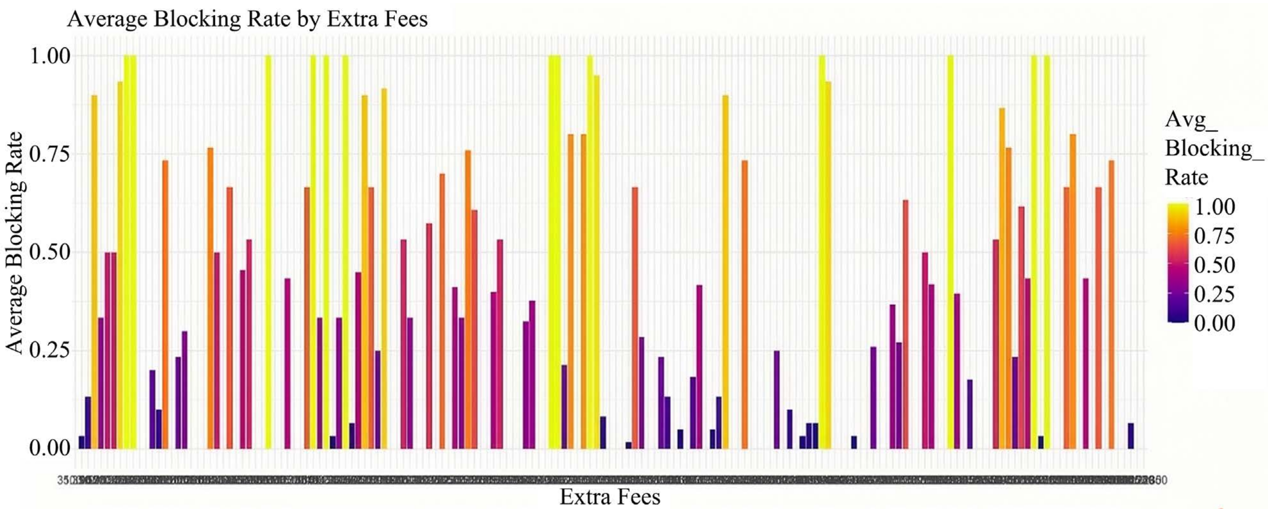

Figure 15. The effect of all extra fees on blocking status. Source: Elaborated by the authors.

The analysis implies that having security deposits and cleaning fees is linked to a lower likelihood of Airbnb listings being blocked. Several reasons could contribute to this observation. Firstly, listings prioritizing cleanliness and guest satisfaction might attract more bookings, resulting in fewer blocked days. The existence of cleaning fees and security deposits may indicate hosts' dedication to providing a high-quality experience, positively influencing guest perception, leading to increased bookings and fewer blocked days. Moreover, higher overall quality often translates to better reviews and increased guest satisfaction, making listings with positive reviews and high ratings more appealing and less prone to being blocked.

Secondly, higher cleaning fees might dissuade some guests from making reservations. The resulting increased availability, due to potentially fewer bookings, decreases the likelihood of blocking certain dates. Listings with cleaning fees and security deposits may signify upscale accommodations, attracting discerning guests willing to pay these fees. Consequently, hosts may avoid blocking their properties frequently to maximize revenue. Additionally, guests who choose such properties may prefer longer stays, justifying the higher cleaning fee and security deposit, resulting in fewer turnovers between guests. This reduces the need for frequent blocked dates to accommodate cleaning and preparation.

8.2.4. Booking Volume & Annual Revenue

An analysis of a dataset containing various attributes related to property rentals is conducted, with preprocessed dataset to ensure compatibility with regression models. Three regression models were applied: Linear Regression, Ridge Regression, and Lasso Regression. The target variables for these models were the "Number of Bookings LTM" (Booking Volume), "Annual Revenue LTM" (Annual Revenue), and the binary "B" status (Blocking Status). Multiple features, including property types, various rates, occupancy-related metrics, and ratings, were considered as predictors.

Results Interpretation:

*Results Visualization:

The residual plots show the relationship between the fitted values and the residuals for each of the regression models (booking volume, annual revenue, and blocking status).

- X-Axis: Fitted values (predicted value).
- Y-Axis: Residuals (differences between actual value and predicted value).
- Interpretation: This plot shows how well the regression model predicts the actual value. If the points are randomly scattered around the dashed red line (which represents a zero residual), it suggests that the model's assumptions are met and the predictions are unbiased.

Booking Volume Regression:

As shown in Figure 16, an increase in the number of bedrooms and being located in the Stuyvesant Town neighborhood are associated with higher booking volumes, while higher prices and certain property types are associated with lower booking volumes, just like what Figure 16 displayed.

Annual Revenue Regression:

Higher prices, certain property types, more bedrooms, being located in the Stuyvesant Town neighborhood, higher counts of reservation days, and higher nightly rates are associated with higher annual revenue, as proved in Figure 17.

Blocking Decision Regression:

Shown in Figure 18, the factors that positively impact blocking includes higher prices, certain property types ("Bed & Breakfast", "Condominium"), higher bedroom and bathroom counts, higher overall rating, and higher published nightly, weekly, and monthly rates. On the other hand, having the listing type as "Private room" and more reservation, available, and blocked days have a negative impact on blocking.

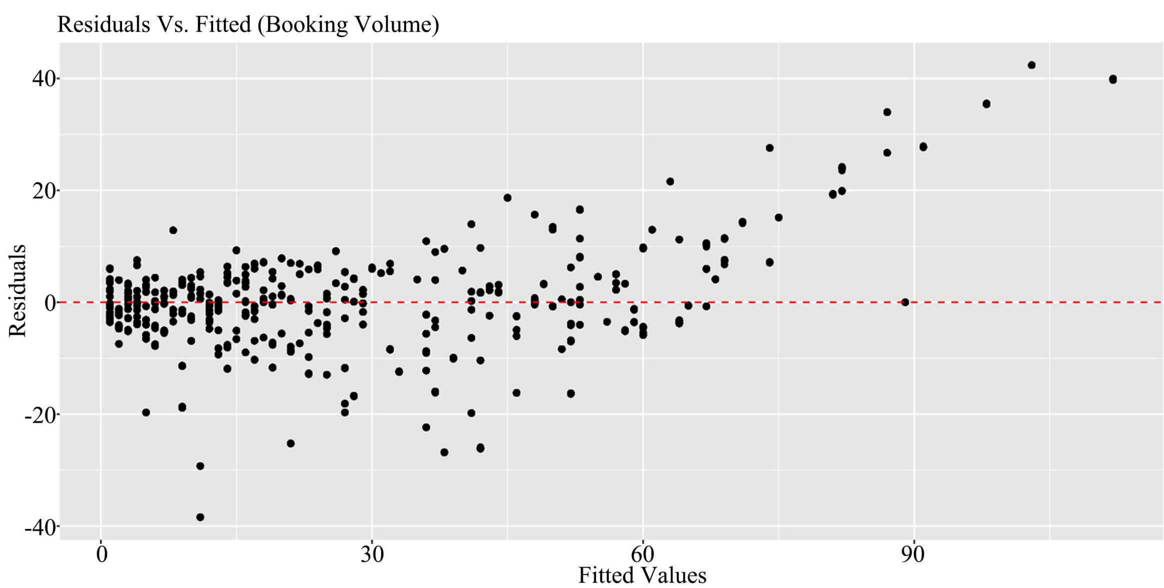

Figure 16. Evidence showing the predictions are unbiased. Source: Elaborated by the authors.

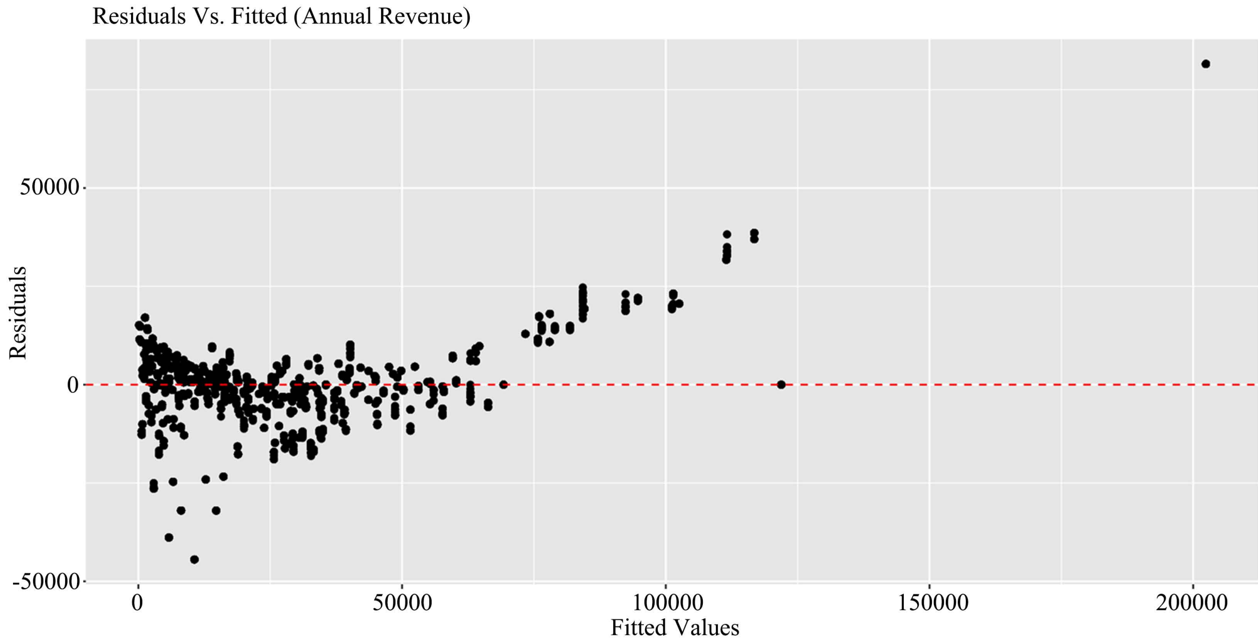

Figure 17. Evidence showing the predictions are unbiased. Source: Elaborated by the authors.

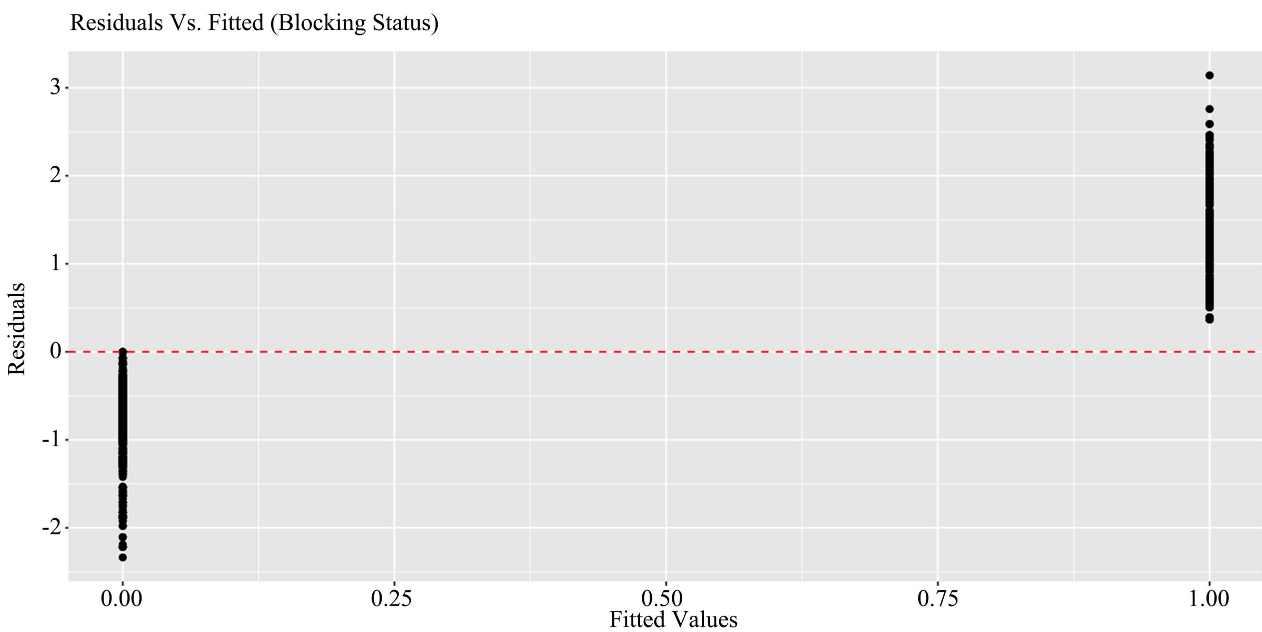

Figure 18. Evidence showing the predictions are unbiased. Source: Elaborated by the authors.

8.3. Factors Influencing Booking Volume, Revenue, and "B" Status

Certain factors may impact booking volume, annual revenue, and the likelihood of a property being blocked ("B" status). While some factors might have similar effects across these three outcomes, others might exhibit different relationships.

Firstly, the pricing strategy plays a pivotal role in shaping these outcomes. Lower prices can attract budget-conscious travelers, resulting in higher booking volumes, while higher prices can lead to increased revenue per booking. Surprisingly, higher prices were linked to a lower likelihood of properties being blocked, potentially because guests are less inclined to cancel reservations when they've paid a premium rate.

Secondly, the type of property impacts the dynamics of booking. Specific property types, such as "Bed & Breakfast" and "Loft," tend to attract more bookings, while others like "Townhouse" experience lower booking volumes. Property type not only influences booking numbers but also plays a substantial role in annual revenue, with popular property types generating more revenue due to higher demand. However, the relationship between property type and blocking behavior varies; for instance, "Loft" properties were more likely to be blocked, possibly due to their popularity and limited availability.

Furthermore, guest reviews and ratings significantly affect booking volume and annual revenue. Higher ratings are associated with an increase in booking volume, indicating that positive guest experiences contribute to a property's reputation and attract more guests. This also translates into higher annual revenue, as satisfied guests tend to rebook and share positive word-of-mouth, ultimately driving revenue. Moreover, higher ratings lead to a decrease in the odds of a property being blocked, suggesting that properties with better ratings tend to attract more committed guests who are less likely to cancel reservations, thereby reducing the need for hosts to block their properties.

Another critical factor is the published rates (nightly, weekly, and monthly). Higher rates often result in lower booking volumes because they can deter potential guests. On the other hand, lower published rates lead to reduced annual revenue, as the revenue per booking decreases. Interestingly, higher published rates are linked to a decrease in blocking likelihood, indicating that guests who are willing to pay more may be more committed to their bookings.

The presence of a security deposit influences revenue and blocking. While there is no direct relationship between security deposits and booking volume, higher security deposits are associated with increased annual revenue, possibly because guests are more committed to bookings when a significant deposit is at stake. Notably, higher security deposits are linked to a decrease in blocking, as guests are less likely to cancel under such circumstances, and hosts may be motivated to keep their properties open.

Additionally, the neighborhood in which a property is situated plays a role in blocking behavior. The "Stuyvesant Town" neighborhood was less likely to be blocked, suggesting that hosts in this area have confidence in maintaining consistent bookings.

Furthermore, the number of blocked days has a significant impact on booking volume and annual revenue. A higher count of blocked days is associated with lower booking volumes, ultimately affecting annual revenue negatively. Hosts who frequently block their properties may have fewer available days for guests to book, leading to a decrease in both volume and revenue. Interestingly, a higher count of blocked days in the last 12 months is associated with an increase in the odds of blocking. Hosts who frequently block their properties may be more selective or have specific availability periods.

Another key factor is the annual revenue in the last 12 months, which reflects the demand for a property and its ability to generate bookings. Higher annual revenue is an indicator of a strong history of bookings and positive reviews, attracting guests to the property. Such properties are also more likely to have fewer blocked days, as hosts are motivated to keep their properties open to maintain their income.

Surprisingly, higher booking volumes were associated with an increased likelihood of blocking. This suggests that properties with high demand may implement stricter booking policies, potentially leading to more blocked days.

Lastly, other factors such as response rate and cleaning fees have less significant impacts on the blocking status compared to the aforementioned factors. A high response rate positively influences booking volume and annual revenue, as guests appreciate timely responses that lead to quicker decision-making. The impact of cleaning fees on booking volume and annual revenue depends on their competitiveness compared to similar listings; a reasonable fee does not deter guests, while a high fee may influence potential bookings.

In summary, various factors play a crucial role in shaping booking volume, annual revenue, and the likelihood of properties being blocked. These factors interact in complex ways, ultimately influencing the performance and profitability of Airbnb listings.

9. Conclusion

This research has provided a thorough analysis of the transformative force of the sharing economy, with a particular focus on the prominent platforms, Airbnb. Through an examination of the operational dynamics, impacts on traditional industries, and implications for societal welfare, valuable insights into the complexities of this innovative economic model are gained.

The study has highlighted the significant advantages offered by the sharing economy, such as flexibility for workers, increased variety and affordability for consumers, and opportunities for entrepreneurship and resource optimization. Platforms like Uber and Airbnb have reshaped traditional notions of work and accommodation, challenging established industries while creating new opportunities for economic empowerment and sustainability.

However, alongside these benefits, the research has also underscored the challenges and complexities inherent in the sharing economy. Concerns surrounding labor rights, income stability, regulatory frameworks, and data privacy remain pressing issues that require careful consideration and robust policy interventions. Most importantly, the analysis of property blocking behavior on Airbnb has shed light on the intricacies of supply dynamics and revenue optimization within the platform, highlighting the need for further research and strategies to enhance efficiency and profitability for hosts.

Despite these challenges, the sharing economy continues to evolve and expand, presenting both opportunities and challenges for stakeholders across various sectors. As the sharing economy landscape continues to evolve, it is imperative for policymakers, industry stakeholders, and researchers to collaborate in developing innovative solutions that maximize the benefits of this economic model while addressing its inherent challenges.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Bock, T. (2022). *How to Interpret Logistic Regression Coefficients.* Displayr. https://www.displayr.com/how-to-interpret-logistic-regression-coefficients/.

Byers, J. et al. (2013). The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Electronic Journal.* https://doi.org/10.2139/ssrn.2366898.

Chen, M. K. et al. (2017). The Value of Flexible Work: Evidence from Uber Drivers. NBER Working Paper No. 23296. https://doi.org/10.3386/w23296.

Cheng, M. M., & Foley, C. (2018). The Sharing Economy and Digital Discrimination: The Case of Airbnb. *International Journal of Hospitality Management, 70,* 95-98. https://doi.org/10.1016/j.ijhm.2017.11.002.

Farronato, C., & Fradkin, A. (2018). The Welfare Effects of Peer Entry in the Accommodation Market: The Case of Airbnb. NBER Working Paper 24361. https://doi.org/10.3386/w24361.

Fraiberger, S. P., & Sundararajan, A. (2015) Peer-to-Peer Rental Markets in the Sharing Economy. *Electronic Journal.* https://doi.org/10.2139/ssrn.2574337.

Guo, Y., Chen, J., Zhou, Y., & Geng, J. (2020). Sharing Economy Platforms' Pricing Strategies and Decision Preferences: The Example of DiDi. *Open Journal of Business and Management, 8,* 1641-1656. https://doi.org/10.4236/ojbm.2020.84104

Hanzy, H., & Li, K. (1965, January 1). *Logistic Regression Intercept Adjusting Average Fitted Probabilities.* Cross Validated. https://stats.stackexchange.com/questions/357662/logistic-regression-intercept-adjusting-average-fitted-probabilities

ny_april_10009_HAN (n.d.). https://app.airdna.co/data/us

ny_10009_HAN. AirDNA. (n.d.). https://app.airdna.co/data/us

Appendix A

To prepare the data for the logistic regression analysis, several preprocessing steps were performed to ensure data quality and model suitability.

Due to the nature of the dataset and the goal of the analysis, certain independent variables, such as "…1.x", "Date", "BookedDate", "Listing Title", "Created Date", "Zipcode", "Metropolitan Statistical Area", "Calendar Last Updated", "Check-in Time", "Checkout Time", "Listing URL", "Listing Main Image URL", "price_norm," and "photo_room_ratio" were excluded from the analysis. These variables were deemed irrelevant or uninformative for predicting the status of the Airbnb listings.

Secondly, for "Security Deposit", "Cleaning Fee" and "Extra People Fee," the "NA" value for those columns are changed to 0, since "NA" indicates that the Airbnbs would not charge such fees.

Furthermore, for "Property Type," "Listing Type," "Neighborhood," "Superhost," "Cancellation Policy," "Business Ready," and "Instantbook Enabled," the character are changed to factor. While for "Overall Rating," "Response Rate," "Response Time (min)," and "Published Weekly Rate," the characters are changed to the number.

After all, all the "NA" are omitted in the last result, nyp4.5. In this way, the dataset was appropriately prepared for the logistic regression analysis, and any potential biases or issues that could affect the model's performance were minimized.

Appendix B

To prepare the data for the logistic regression analysis, several preprocessing steps were performed to ensure data quality and model suitability. Due to the nature of the dataset and the goal of the analysis, certain independent variables, such as "…1," "PropertyID," "Date," "BookedDate," "ReservationID," "Year," and "Month," were excluded from the analysis. These variables were deemed irrelevant or uninformative for predicting the status of the Airbnb listings. In this way, the dataset was appropriately prepared for the logistic regression analysis, and any potential biases or issues that could affect the model's performance were minimized.