<u>Racial Discrimination in the Sharing Economy:</u>

<u>An Economic Analysis of New York City Airbnb Listings</u>

By

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Abstract

Over the past decade, advances in technology have begun to change the way in which transactions of goods and services occur in the marketplace. These changes have paved the way for a new market of collaborative consumption, often called the "sharing economy," in which consumers share their goods with other consumers who would otherwise seek out traditional producers. Within this sharing economy has emerged Airbnb, a social marketplace that connects hosts looking to share their homes with prospective guests searching for travel accommodations. While Airbnb provides a wide diversity of accommodations across the globe, offering lower prices and more diverse options than traditional hotels, it has also paved the way for unequal opportunity for those looking to receive an extra income by renting their property. The present study examines the phenomenon of racial discrimination in 500 Airbnb listings located in Metro New York City from October 11, 2015 to October 11, 2016. The results of my analyses show that White hosts are able to charge 7.21% higher and receive annual occupancy rates 6.18% higher than non-White hosts. These results imply that the sharing economy facilitates racial discrimination, and that services such as Airbnb should consider this problem in constructing their business models.

I. Introduction

In recent years, innovations in technology have fostered the advent of a new form of collaborative consumption often dubbed the "sharing economy." This economic activity includes the sharing of one's own, personal goods with consumers who would otherwise seek out conventional sources. The communication and transactions involved in the sharing economy generally take place on mobile apps such as Uber, which functions in a similar manner to a taxi service, allowing travelers to contact certified drivers at the touch of the button. In this study, I will be examining Airbnb, a service that connects hosts with travelers searching for accommodations. These hosts rent out extra rooms in their home, or entire apartments, for brief periods of time. The advent of Airbnb has not only provided an opportunity for people with extra space to make extra income, but also presented consumers with a far wider range of options for travel accommodations. Instead of booking rooms in conventional hotel chains, travelers can now search through thousands of options of apartments and rooms, ranging widely in characteristics and price. These options are very easy to browse on a phone or computer. While the sharing economy has created a wide range of opportunities for both hosts and consumers, it may also come with a cost.

This study aims to answer the question of whether or not the sharing economy presents an equal opportunity for people of all different backgrounds; in particular, does the race of the host influence whether or not consumers will book an Airbnb accommodation? Considering that information about hosts and guests is public, accommodations have a "face" to them unlike conventional hotels. Therefore, guests may take the characteristics of hosts into consideration when booking travel accommodations. This factor brings about the potential for racial discrimination under the Airbnb platform.

To provide one small example suggesting that racial discrimination might be a factor on Airbnb, an African American woman from Chicago named Quirtina Crittendon recently spoke out about her experience with using Airbnb, and in particular, the discrimination she has faced (Vedantam 2014). She states that, after making offers to hosts, she frequently receives negative responses containing excuses, such as another guest sent in an offer just before her; however, she would later find the accommodations left vacant for her dates of interest. So she conducted her own small-scale experiment: Quirtina changed her profile name to Tina, and changed her photograph to a landscape. After making these changes, the problems she was facing diminished, and she faced a higher success rate when making offers to hosts; however, she did not test this experiment statistically (Vedantam 2014).

While some academic studies have looked at racial discrimination in the context of Airbnb, they have not looked at the actual sales of accommodations; rather, they looked at the differences in price charged by hosts of different races. While researchers use this phenomenon as a representation of discrimination, many other factors may contribute to differences in pricing. This paper examines differences in annual occupancy rates, thus presenting a clearer picture of potential discrimination in Airbnb. The results of the included analyses find that White hosts receive annual occupancy rates 6.18% higher than non-White hosts, while also charging 7.21% higher rates, thus indicating the presence of racial discrimination on Airbnb.

II. Literature Review

In his 1957 book titled "The Economics of Discrimination," Gary Becker presented the first economic model of discrimination in the marketplace. Becker claimed that individuals have “tastes for discrimination,” which bring about discriminatory behaviors against individuals based on their race, religion, sex, social class, personality and a variety of other characteristics. An individual conducts discrimination of this nature when one acts as if he or she incurs a non-monetary, psychical cost of interacting with them. This discrimination only occurs in situations of direct contact between both parties. Becker presents an example of this discrimination involving employers discriminating against potential employees. According to Becker, an employer discriminates when paying employees at a rate that is not directly proportional to the market rate due to added discrimination costs. He presents a model of net wage, $W = \pi(1+d)$, where W is the market wage, π is the wage rate and d represents the employer’s taste for discrimination. If W is less than $\pi(1+d)$, only the employee for whom the employer does not have a taste for discrimination against will be hired, provided that both options of employees are perfect substitutes in production (Becker 1957).

When Becker’s model is applied to the present study, a guest, the employer, who comes across an Airbnb listing with a non-White host is said to discriminate when he or she acts as if staying with the non-White hosts costs them an extra, non-monetary value. This cost is then factored into the guest’s decision as to whether or not to book an accommodation. If the discriminating guest is able to find an Airbnb owned by a host for whom the guest does not hold a taste for discrimination against for an equal price and with equal qualities to one owned by a host which the guest holds a taste for discrimination against, he will choose the former option over the latter. However, if the former option costs more than the latter, the price difference must be less than the added cost brought on by the guest’s taste for discrimination against the other host.

The present study tests the presence of racial discrimination by use of the hedonic pricing approach. On Airbnb, guests are effectively shopping for temporary homes. Properties differ in size, layout, location, and included amenities, and are priced accordingly. The hedonic approach determines the price of each of these individual characteristics that are included in a home by use of a linear regression that predicts the total price (O'Sullivan 284). One of the earliest examples of the hedonic pricing approach in practice is John Kain and John Quigley's (1970) study of housing prices in St. Louis. They regressed market prices of both owner and renter occupied units on 39 characteristics that represented the quality of each housing bundle. These 39 variables included seven measures of the quality of households (i.e. condition of floors, walls, windows, etc.), seven measures of the quality of the structure (i.e. condition of driveways and walkways, landscaping, etc.), eight measures of the quality of surrounding properties (i.e. condition of structures, parcels, etc.) and 17 measures of the quality of the block (i.e. condition of street, percent vacant, trash on block, etc.).

Kain and Quigley (1970) found that the residential services surrounding a property have an effect on the price of the housing bundle similar to characteristics of the actual dwelling, such as number of bedrooms and bathrooms. These residential services included accessibility to employment, neighborhood environment, schools, garbage collection, police protection, and more. The results of their regression analysis found, for example, that households with hot water are priced at $4.89 higher per month than ones with cold water, and that central heating increases rent by $4.59 monthly. Also, the difference between a two and three-bedroom unit averages $10.17 per month (Kain and Quigley 1970). While they included a wide variety of variables indicating the quality of the dwellings in question, they did not include personal information, such as ethnicity, about the tenants and landlords or sellers involved. As seen in Becker's (1954) theory, discrimination can impact prices if the parties involved hold tastes for discrimination. The present study takes the factor of host race into account in an effort to determine the economic costs of racial discrimination on Airbnb, by conducting a similar analysis to that seen in Kain and Quigley's (1970) study.

Various studies have examined the impact of discrimination in the sharing economy, particularly in the context of Airbnb. The recent study by Lee, Hyun, Ryu, Lee, Rhee and Suh (2015) examined the impact of features associated with the sale of Airbnb accommodations. The study included data from 4,178 rooms across five major cities in the United States: New York City, Chicago, Los Angeles, San Francisco and Seattle. In order to measure the number of sales of each unit over the two-month period of data collection, they used the change in number of reviews on each unit ("review delta") as a proxy for the minimum number of reservations over the time period. They collected data on August 1st and October 1st of 2014 in an effort to capture this change in reviews. Since sale data is not public, and reviews can only be written after an accommodation is booked, this data point appears to be an acceptable proxy for sales.

The model presented in their study includes a linear regression involving a multitude of predictors, categorized as either "social factors" or "room factors," that were used to predict "review delta." Room factors included characteristics of each physical unit, such as the number of bedrooms, the number of beds, and the price per night. The social factors provided characteristics of the host and his or her interactions with prior guests, such as the number of reviews on the listing and the host's average response time upon receiving messages from potential guests. The results of their study found a multitude of factors that were significant in predicting room sales. Social features that mattered included the average response time of the host, the number of times the listing has been added to other guests' wish lists, the number of reviews on the listing, and the membership seniority of the host. Other significant predictors included whether or not the accommodation included a TV, air conditioner, shampoo, essentials, cleaning fees and a minimum stay requirement. They did not include the results for the price variable in the study. Although they included a wide variety of social factors, Lee et. al. neglected to include information about race of each respective host, so they could not test for racial discrimination with their data set.

Ert, Fleischer and Magan (2016) further examined the impact of social features and their impact on Airbnb listings in their recent study that assessed the role of personal photos on Airbnb. The study aimed at answering the question as to whether or not consumers infer sellers' trustworthiness from their personal photos, a process that they describe as "virtual-based trust", as well as the sellers' perceived attractiveness. In turn, they hypothesized that this visual-based trust and attractiveness impacts consumers' decision making as to whether or not to book an accommodation. In order to conduct this analysis, they collected similar photographs of 70 amateur actors (35 females and 35 males) and constructed mock Airbnb listings for each one. In an effort to assess the perceived trustworthiness and attractiveness of each host and listing, they employed a group of 31 undergraduate students who rated the 70 actors based on attractiveness and apparent trustworthiness, and 21 undergraduate students who evaluated the photographs of 39 rooms based on whether or not they would rent each accommodation. Ert. et. al. (2016) then gathered 566 Israeli participants from an online panel of 120,000 volunteers who selected preferred accommodations from sets of two of the mock listings.

The results of Ert et. al.'s (2016) mixed logit analysis, which estimated the effect of the visual-based trustworthiness and attractiveness of the hosts on the probability that their listings will be selected, confirmed their hypothesis that visual-based trust affects listing choice. The higher the perceived trust of the host was ranked, the higher the likelihood was that the listing was chosen. Attractiveness, while slightly less significantly positive, affected choice in a similar light. Overall, Ert, Fleischer and Magan found that guests on Airbnb make inferences about hosts based on their profile pictures, which in turn affects the guests' decision of what accommodation to book.

While the aforementioned studies indicate that social characteristics of Airbnb listings impact guests' decision making in picking an accommodation, neither study includes the race of the hosts as a factor. However, some recent studies have examined racial discrimination in Airbnb. For example, Edelman, Luca and Svirsky (2016) conducted an experiment that examined whether or not Airbnb hosts were less inclined to accept offers from African American guests than White guests. In order to do so, they constructed fake profiles of guests with distinctly African-American and White names, and contacted hosts via these accounts with offers. The results of their study found statistically significant results that offers from guests with distinctly White names are accepted roughly 50% of the time, while offers from guests with distinctly African-American sounding names are accepted only 42% of the time. Therefore, they conclude that African-American guests are 16% less likely to be accepted than White guests. These results held across hosts' neighborhoods with varying diversity rates (Edelman et. al. 2016).

While Edelman et. al. (2016) discovered racial discrimination against Airbnb guests, the present study examines racial discrimination by guests against hosts, which Edelman and Luca explored in their previous study (2014). In this study, Edelman and Luca examined whether African-American hosts charge less than White hosts for equivalent rentals, implying that this phenomenon would represent racial discrimination by guests. In order to determine the race of each host, they employed workers on Amazon Mechanical Turk to examine the photo of each host included in the study. The workers coded the race of each host into one of the following categories: White, Black, Hispanic, Asian, Unclear but Non-White, Multiple Races, Not Applicable (no people in picture), or Unclear/Uncertain. They then constructed a dummy variable "Black Host," indicating whether or not each host was perceived as Black, as the variable of interest.

The results of their hedonic pricing model found the dummy variable "Black Host" to be a significant predictor of the listing price with a negative coefficient. They concluded that non-Black hosts are able to charge 12% more for listings with similar characteristics, ratings and photos than Black hosts (Edelman and Luca 2014). While these results may imply discrimination, they assume that hosts all set prices based on the market demand for their listing. Although African-American hosts charge less for similar listings, other factors may be at play in their decision. Therefore, in the present study, I examine whether or not the race of the host predicts occupancy rate instead of price in an effort to more accurately conclude whether racial discrimination influences guests' decision of accommodations.

In a similar study to Edelman and Luca's (2014), Wang, Xi and Gilheany (2015) constructed a hedonic pricing model that examined racial discrimination on Airbnb. Instead of Black hosts, however, they tested to see if Asian Airbnb hosts experience similar discrimination. They collected data on 101 White and Asian hosts in both Oakland and Berkeley, California, in April of 2015. Their model sought to predict whether the number of bathrooms and bedrooms, the number of people the accommodation can fit, the price, and the race of the host (White or Asian) predict the price of each listing. In order to account for host race, they manually sorted through photos of each host and constructed a dummy variable, assigning hosts they perceived as

Asian a 1, and hosts they perceived as White a 0. They omitted any hosts that did not appear to fit in to either of these categories, as well as any hosts for which race was uncertain.

Wang et. al. (2015) confirmed Edelman and Luca's (2014) results, which found that minority hosts face discrimination and therefore charge lower prices than White hosts. However, while Edelman and Luca (2014) conducted their analysis for Black hosts, Wang et. al. (2015) looked at Asian hosts. They found that Asian hosts earn $90 (or 20%) less per week on average than White hosts with similar rentals. Again, while these results may indicate discrimination, price does not appear to be a strong enough indicator of this phenomenon, as it assumes that every host prices their Airbnb at the level demanded by the market. There may exist some reason other than personally experienced racial discrimination as to why non-White hosts price their listings lower than White hosts. For example, they may simply be assuming that guests are less inclined to stay with them due to their ethnicity, albeit not applying in practice.

My study examines the phenomenon of racial discrimination in 500 Airbnb listings in the New York City neighborhoods of Astoria, Flatbush, the Lower East Side, Richmond Hill and Washington Heights. My model predicts the annual occupancy rate of each listing from October 11, 2015 to October 11, 2016, and therefore should present a clearer indication of racial discrimination than that found in both Edelman and Luca's (2014) paper and Wang et. al.'s (2015) paper. My model is very similar to that found in Lee et. al. (2015), but includes the ethnicity of each host. My data set includes an expansive list of both social and physical factors involved in each listing that may influence guests' decision as to what accommodation to book. However, while Lee et. al. (2015) used their proxy "delta reviews" to represent room sales, I use an annual occupancy rate. Since not every guest leaves a review, albeit incentivized to do so, my model presents a clearer depiction of total bookings. Furthermore, while Lee et. al. include a wide variety of social factors, they do not include race as a predictor. Since the previously mentioned studies indicated that guests take the race of the hosts into consideration when booking accommodations, I include the race of the host as my variable of interest.

III. Data

In my research, I used a data set of New York City Airbnb listings from October 2016 provided by Airdna (Airdna.com 2016). Airdna is a company based in the United States that provides Airbnb data and analytics to vacation rental entrepreneurs and investors. They track the daily performance of over 2,000,000 listings across roughly 5,000 cities around the globe. This data set provided me with the occupancy rates that I needed to properly conduct my analyses. The original data set provided by Airdna included information on 118,530 listings in the New York City area. Since one of the data points in my study includes the occupancy rate over the previous 12 months, from October 11, 2015 to October 11, 2016, I removed a total of 43,083 listings that were created during those 12 months. This ensured that the occupancy rate accounted for the entire year. I then removed 63,665 listings that were no longer active, and therefore did not provide data for the past year. Of the remaining listings, 3,080 provided incomplete data, and I removed them as well. After this initial trimming process, 8,702 listings remained.

As seen in Lee, Hyun, Ryu, Lee, Rhee and Suh's (2015) study on social and physical factors associated with the sale of Airbnb listings, certain physical attributes, including amenities, matter to guests when booking accommodations. Therefore, I wanted to include all potential amenities in my model. These amenities include free parking, an elevator, 24-hour check-in, a pool, a doorman, an indoor fireplace, internet, a gym, wheelchair accessibility, a hot tub, wireless internet, breakfast, a kitchen, cable TV, a washer, a dryer, a buzzer, a laptopfriendly workspace, an iron, hangers, a hairdryer, a TV, shampoo, heating, essentials, air conditioning and whether or not the listing is accepting of pets, families and events. The inclusion of these amenities or lack thereof is public on every listing, but the data set provided by Airdna did not include them. In order to include them, I needed to access each individual listing and determine whether or not each amenity was provided.

After trimming the data set down to a total of 8,703 listings with complete data points, I began collecting data on individual listings. The process of accessing individual Airbnb listings and recording the presence of individual amenities is highly time intensive. Due to the time constraints surrounding this project, I could not collect data points for all remaining 8,703 listings. I set a reasonable goal of including 500 listings. I selected five neighborhoods in New York City based on perceived diversity to examine. By selecting five neighborhoods instead of randomly selecting listings from the entire data set, I am also able to control for individual differences of the neighborhoods, such as perceived safety.

Along with data points on individual amenities, I needed to add information on the race of the host. While Edelman and Luca (2015) used “Black Host” as their variable of interest, indicating whether or not each host was Black, and Wang, Xi and Gilheany (2015) used an indicator of whether or not each host was Asian, I decided upon using “White” as my independent variable of interest, describing whether or not the host is perceived as White. I saw this as a greater representation of discrimination as a whole, as all non-White groups are generally believed to experience discrimination. Another issue that I ran into is the fact that information on race is not required in host biographies. In order to determine the race of Airbnb hosts, Wang, Xi and Gilheany simply looked through the included profile pictures and labeled hosts as White or Asian. Those hosts that did not appear to be in either group, as well as those for whom race was not clear, were removed from the study. Considering they deemed this method adequate, I carried out the same process. I sorted through each listing in my data set and labeled them as having a White or non-White host, and skipped over any listings for which the race of the host was ambiguous to me, with the goal of reaching 500 total listings. Furthermore, any listings that did not have a picture of the actual host, as well as those depicting multiple individuals of different ethnicities, were also left out from the data set. This resulted in a total of 55 unused listings. Many listings included descriptions of the hosts' respective ethnic origins, which further improved the accuracy of my observations. The final data set of 500 Airbnb listings included the following number of listings from each neighborhood: 117 in Astoria, 102 in Flatbush, 182 in the Lower East Side, 11 in Richmond Hill and 88 in Washington Heights.

With a longer project timeline and no budget constraint, I ideally would have hired workers on Mechanical Turk to examine each host's photo and determine their respective races, as was done in Edelman and Luca's (2014) study. This process would have reduced bias and provided strong inter-rater reliability; however, it was not feasible for this project. Due to time constraints of the project, I personally collected data on a total of 500 listings.

As part of my analysis, I ran a correlation matrix on all of my variables in an effort to discover any covariance that may impact my results. The results of the correlation results provided a few significant correlations. Namely, the variable Iron presented a significant positive relationship with both Hangers ($r = 0.7679$) and Hairdryer ($r = 0.7396$), and Hangers presented a significant positive correlation with Hairdryer ($r = 0.7544$). While these variables present significant positive relationships, my analysis should suffer little consequences, as they are not the most important variables in my regressions. Rather, White, OccupancyRateLTM and lprice are my most important variables of interest, and none of them presented any significant relationship with other variables in the analysis. Therefore, I found it unnecessary to include the results of my correlation matrix in the study.

IV. Model

The present study includes three linear regression models. The first is a simple hedonic pricing model matching to the best extent possible that of the Wang et. al. (2015) study. The model predicts the price of each listing, and includes the following:

$$lprice_i = \beta_0 + \beta_1 sqrtlbedrooms_i + \beta_2 whiteq_i + \beta_3 lmaxguests_i + \beta_4 lbathroomssq_i + \varepsilon_i$$

Variable transformations, descriptions and statistics are provided in Table 1. While this model may provide some indication as to whether or not guests select their accommodations based on the race of the host, it includes a very limited number of variables. In turn, the model presents the potential for omitted variable bias. Omitted variable bias occurs when a predictor variable that is correlated with other repressors and partially determines the dependent variable is left out of the analysis. By leaving these predictors out, the model provides biased results of the coefficient on the included variables (Stock and Watson 2007). Since each Airbnb accommodation includes a diverse basket of characteristics and amenities, I felt as though the model listed above did not present a comprehensive prediction of price. In order to address the potential omitted variable bias involved in the first model, I created a second one that includes a wide variety of new variables that may influence the price of a listing, such as ratings and reviews, neighborhoods, property types and included amenities. This model contains the following:

$$lprice_i = \beta_0 + \beta_1 sqrtlbedrooms_i + \beta_2 whitesq_i + \beta_3 lmaxguests_i + \beta_4 lbathroomssq_i + \beta_5 lOccupancy_i + \beta_6 CreatedDate_i + \beta_7 OverallRating_i + \beta_8 NumberofReviews_i + \beta_9 ResponseRate_i + \beta_{10} Superhost_i + \beta_{11} SecurityDeposit_i + \beta_{12} CleaningFee_i + \beta_{13} ExtraPeopleFee_i +$$

$\beta_{14}MinimumStay_i + \beta_{15}NumberofPhotos_i + \beta_{16}Instabook_i + \beta_{17}White_i + \beta_{18}FreeParking_i + \beta_{19}Elevator_i + \beta_{20}Pets_i + \beta_{21}HrCheckin_i + \beta_{22}FamilyFriendly_i + \beta_{23}Pool_i + \beta_{24}Smoking_i + \beta_{25}Doorman_i + \beta_{26}SuitableforEvents_i + \beta_{27}IndoorFireplace_i + \beta_{28}Internet_i + \beta_{29}Gym_i + \beta_{30}Wheelchair_i + \beta_{31}HotTub_i + \beta_{32}WirelessInternet_i + \beta_{33}Breakfast_i + \beta_{34}Kitchen_i + \beta_{35}CableTV_i + \beta_{36}Washer_i + \beta_{37}Dryer_i + \beta_{38}Buzzer_i + \beta_{39}LaptopFriendly_i + \beta_{40}Iron_i + \beta_{41}Hangers_i + \beta_{42}Hairdryer_i + \beta_{43}TV_i + \beta_{44}Shampoo_i + \beta_{45}Heating_i + \beta_{46}Essentials_i + \beta_{47}AC_i + \beta_{48}Neighborhood_i + \beta_{49}PropertyType_i + \beta_{50}ListingTypes_i + + \beta_{51}Cancellation_i + \varepsilon_i$

The third model is my own analysis predicting the annual occupancy rate of each listing from October 11, 2015, to October 11, 2016. It includes the following:

$OccupancyRate_i = \beta_0 + \beta_1 White_i + \beta_2 lprice_i + \beta_3 NumberofReviews_i + \beta_4 Bedrooms_i + \beta_5 Bathrooms_i + \beta_6 MaxGuests_i + \beta_7 ResponseRate_i + \beta_8 Superhost_i + \beta_9 SecurityDeposit_i + \beta_{10}CleaningFee_i + \beta_{11}ExtraPeopleFee_i + \beta_{12}MinimumStay_i + \beta_{13}NumberofPhotos_i + \beta_{14}Instabook_i + \beta_{15}CreatedDate_i + \beta_{16}FreeParking_i + \beta_{17}Elevator_i + \beta_{18}Pets_i + \beta_{19}HrCheckin_i + \beta_{20}FamilyFriendly_i + \beta_{21}Pool_i + \beta_{22}Smoking_i + \beta_{23}Doorman_i + \beta_{24}SuitableforEvents_i + \beta_{25}IndoorFireplace_i + \beta_{26}Internet_i + \beta_{27}Gym_i + \beta_{28}Wheelchair_i + \beta_{29}HotTub_i + \beta_{30}WirelessInternet_i + \beta_{31}Breakfast_i + \beta_{32}Kitchen_i + \beta_{33}CableTV_i + \beta_{34}Washer_i + \beta_{35}Dryer_i + \beta_{36}Buzzer_i + \beta_{37}LaptopFriendly_i + \beta_{38}Iron_i + \beta_{39}Hangers_i + \beta_{40}Hairdryer_i + \beta_{41}TV_i + \beta_{42}Shampoo_i + \beta_{43}Heating_i + \beta_{44}Essentials_i + \beta_{45}AC_i + \beta_{46}Neighborhood_i + \beta_{47}PropertyType_i + \beta_{48}ListingTypes_i + \beta_{49}Cancellation_i + \beta_{50}OverallRating_i + \varepsilon_i$

Variable information and descriptive statistics for all of the variables included in the models above are provided in Table 1.

V. Results

The results from my first regression analysis are provided in Table 2. The predictors involved in this regression present an R-squared of 0.3809, which implies that the regression predicts 38.09% of the variability in listing prices. My model confirms a relationship between ethnicity and listing price, thus confirming the findings of Wang, Xi and Gilheany's (2015) paper and Edelman and Luca's (2014) paper, as my variable whitesq proved to be a statistically significant predictor of price. White hosts on average charge 17.53% higher prices than non-White hosts for listings with similar characteristics, which is slightly less economically significant than the 20.13% figure in Wang et. al. (2015), despite our use of a highly similar model. Other statistically significant variables included sqrtlbedrooms and loccupancy, while lbathroomssq was not significant. A one percent increase in the number of bedrooms leads to a 35.87% increase in price, and a one percent increase in the number of guests allowed leads to a 48.08% increase in price. Along with being economically significant, these results both make sense, as both variables indicate the size of the Airbnb. As the size of an accommodation increases, the price should as well.

The results of my first regression directly parallel those of Wang et. al. (2015), who found a statistically significant negative coefficient indicating that Asian hosts charge lower prices than White hosts. However, our variables provide differing economic significance. Aside from the race variable, the extent to which a one percent change in bedrooms increased price was 21.38 percentage points lower in my study than in Wang et. al. (2015). In contrast, a one percent change in allotted guests led to a change in price 13.7 percentage points higher in my data than in than in Wang et. al. (2015). While these results differed in economic significance, the coefficients hold similar signs and statistical significance. Thus, I confirmed the accuracy of their conclusion, and found that their results apply over differing geographical locations. However, this model is not perfect. It includes strange variable transformations that I saw as unnecessary for the analysis. The model also provides little detail on the physical characteristics of each listing, as well as certain social factors; therefore, I believe it may represent omitted variable bias. In order to remove this bias and improve the test of racial discrimination, I constructed a stronger model including far more social and physical features of each listing that predicts the price of each listing.

The results of my second regression are shown in Table 3. The new model presents an R-squared of 0.7977, implying that the regression predicts 79.77% of the variability in listing prices. Despite adding many new variables to the prior model, some of the results held. In this regression, whitesq and lmaxguests again present positive coefficients that are significant at the 99% confidence level. According to the model, White hosts charge 7.21% higher prices than non-White hosts for listings with similar characteristics. This figure is still positive and significant, and the extent to which White hosts charge more than non-White hosts has increased from the prior model. This suggests that the first model did indeed present omitted variable bias. Further, a one percent increase in the maximum number of guests allowed predicts an 19.02% price increase, which fell from the 48.08% figure in the prior analysis, and a one percent increase in the number of bedrooms leads to a 16.60% increase in price, which fell from the 35.87% figure in the prior analysis. The fact that both of these figures fell in the secondary analysis further confirms the omitted variable bias in the first analysis. This figure still makes sense, as accommodations that allow more guests are likely larger, and therefore cost more. Other significant positive predictors in this model included Superhost, CleaningFee, NumberofPhotos, Hairdryer, Breakfast, Buzzer, SecurityDeposit, Neighborhoods3, PropertyTypes3, ListingTypes1, and ListingTypes2, and significant negative predictors included MinimumStay, LaptopFriendly, Neighborhoods2, Neighborhods4, and OccupancyRateLTM. The majority of these results aligned with my expectations, albeit a few outliers.

As demonstrated in past studies, the sharing economy is built on a system of trust between buyers and sellers. One method that hosts on Airbnb can signal that they are trustworthy is by receiving the "Superhost" designation, which implies that they have rented their accommodations to a large number of guests. Therefore, Superhosts are highly experienced, and other guests appear to trust them. Hosts that have received the "Superhost" designation charge 8.99% higher prices than those who have not, and guests are willing to pay this added cost to stay with someone they can trust.

As expected, hosts tend to price their accommodations based on the neighborhood in which it resides. Accommodations located in the Lower East Side of Manhattan are priced 45.98% higher than those in Washington Heights. On the contrary, hosts located in Richmond Hill and Flatbush charged 27.15% and 9.43% less than hosts with similar accommodations in Washington Heights, respectively. These results provide insight as to the quality of each neighborhood and the their respective demands for lodging.

Along with the respective neighborhoods in which the Airbnb listings reside, the type of property involved predicts the price. As one would expect, the listing type with the largest, positive, significant coefficient that the accommodations provide is an entire private living space. Specifically, listings that provide an entire living space are priced 84.86% higher than those representing rooms shared with other guests. To a lesser, yet economically significant extent, listings that represent private rooms in the host's home are priced 48.53% higher than those of a shared living space. Guests likely want their own private space to sleep and store their belongings, and hosts price these accommodations accordingly. However, guests are willing to pay the highest price for their own, private dwelling.

While most of these results were in line with expectations, others provided surprising results. Airbnb's that provide a laptop friendly workspace were priced 8.88% lower than those that did not. I cannot understand why this is the case, as having LaptopFriendly was not correlated with any other variables in the study. Similarly, I found it surprising that a one percent increase in occupancy rate led to a 45.15% decrease in price. While these low prices might be attracting guests, one would expect these hosts to raise their prices, as guests may view their listings as underpriced.

The results of my third regression are displayed in Table 4. In this model, I change the dependent variable from lprice to OccupancyRateLTM, as I believe the occupancy rate of a listing over the previous 12 months will provide greater insight into the possibility of racial discrimination on Airbnb than the prices of listings. The adjusted R-squared for my model was 0.3272, implying that the included independent variables explained 32.72% of the variation in occupancy rates. The variable of interest in my model, White, was statistically significant and positive, implying that guests take the race of the hosts into account when booking accommodations. Specifically, White hosts received an occupancy rate 6.18% higher than non-White hosts over the previous 12 months. Therefore, I conclude that racial discrimination is present on Airbnb. Other statistically significant positive coefficients included CreatedDate, OverallRating, NumberofReviews, ResponseRate, Minimum Stay, Instabook, Pool, and Neighborhood3, PropertyType5 and PropertyType6, while lprice, ListingTypes2, ListingTypes3, ExtraPeopleFee, WirelessInternet, and SuitableforEvents were all significant and negative.

As one might expect, the coefficients for OverallRating, NumberofReviews, ResponseRate were all positive. Lee et. al. showed that social features matter to guests when booking accommodations, as they care about the type of person that they will be staying with. A one percent increase in overall rating and number of reviews lead to 7.44% and 0.21% increases in occupancy rate, respectively. This makes sense, as guests want to ensure they can trust whom they stay with, and can build this trust by reading past reviews. Also, a one percent increase in response rate led to a 0.17% increase in occupancy rate. While this figure is not too economically significant, the fact that it is positive and statistically significant is understandable. Responding to guests demonstrates strong customer service, and doing so is necessary to allow guests to book if they are not provided the option of "Instabook."

The coefficient for Neighborhood3, which represents listings located in the Lower East Side of Manhattan, was positive and significant relative to the omitted category, Washington Heights. Airbnb listings in the Lower East Side present a 21.94% higher occupancy rate than those in Washington Heights, despite the fact that accommodations in the Lower East Side are priced at a higher rate, as seen in my prior analysis. The Lower East Side of Manhattan must be a highly desirable destination for guests, as it is commonly known as a hip neighborhood that is close to many tourist attractions.

The coefficients for lprice, ExtraPeopleFee, SuitableforEvents, ListingType2 and ListingType3 were all significant and negative. As expected, tourists on Airbnb generally favor less expensive accommodations, and seek to book listings at decreased prices. A one-percentage point change in price leads to a 25.16% decrease in occupancy rate, so this hypothesis was confirmed. This conclusion is further supported by the result that a one percent increase in the extra people fee leads to a 0.19% decrease in occupancy rate. While this figure is not too economically significant, it shows that guests do not want to pay extra to bring larger parties.

ListingTypes2 and ListingTypes3 represent listings of private rooms and shared rooms, respectively. ListingTypes2, which represents private rooms, present an occupancy rate 15.58% lower than that of the omitted category, ListingTypes1, which represents entire homes or apartments. Similarly, ListingType3, or shared rooms, present an average occupancy rate of 42.72% lower than entire accommodations. In the case of a private room, guests share the accommodation with the host, as well as other potential guests, thus providing them with little privacy. Even less privacy is offered in the case of a shared room, which involves sharing a room with other guests in a similar manner to youth hostels. As shown in my results, guests want privacy, and are willing to pay extra to rent entire private apartments or homes. The cases of SuitableforEvents and WirelessInternet, however, are highly confusing. In a subsequent analysis of correlation, neither SuitableforEvents nor WirelessInternet were correlated with any other variables. Therefore, some other factor must be tied in with these variables that cannot be accounted for.

Interestingly, no coefficients for any of the other included amenities provided statistically significant results. This contrasts the findings of Lee et. al. (2015), who found positive, statistically significant results for the inclusion of a gym, essentials, shampoo, a kitchen, television, air conditioner, an intercom and the ability to bring pets. However, their model predicts delta reviews as a proxy for sales, which may have skewed the results. For instance, guests may be more inclined to write reviews if any of these amenities listed above are included.

Since the overwhelming majority of independent variables in my model were not significant predictors of occupancy rate, I elected to break them into groups and jointly test their significance levels. I divided the variables into five separate groups: Host Characteristics, Listing Characteristics, Property Characteristics, Base Amenities and Luxury Amenities. The contents of each group and their respective results are provided in Table 5. When tested as groups, Host Characteristics, Listing Characteristics, Property Characteristics and Luxury Amenities all proved to be jointly significant predictors of occupancy rate. Therefore, I reject the null hypothesis that each respective variable in the groups do not influence guests' decision making in selecting accommodations. However, Base Amenities were not significant predictors of occupancy rate as a group.

VI. Conclusion

The results of my analyses suggest that there are definite, quantifiable effects of racial discrimination on Airbnb. Specifically, hosts of non-White ethnic backgrounds achieve 6.18% lower occupancy rates and are forced to charge 7.21% lower rates than White hosts for Airbnb listings of similar characteristics. These results are both statistically and economically significant, and suggest severe implications for the sharing economy. The sharing economy presents an unequal opportunity for individuals to take on an extra source of income, in this case, by renting out their homes. While past studies have examined explored racial discrimination on Airbnb, none of them have included occupancy rates in their analyses. By including occupancy rate as my dependent variable, I was able to provide a more accurate picture of whether or not guests take into account the race of hosts when actually booking accommodations.

In order to combat this racial discrimination, Airbnb should alter their model for how listings are either selected or presented. Other various collaborative consumption services present mechanisms that may do so. For example, Uber, a widely used car sharing service, does not allow users to select their drivers. Rather, users are paired with drivers based upon proximity and the type of vehicle necessary, thus preventing users from selecting drivers based upon their ethnicity. If Airbnb were to follow this model, users could input specific accommodation factors that they find necessary, such as a certain number of rooms or access to a gym, as well as a desired geographical location and price range, and Airbnb could match guests with hosts that meet these desired characteristics. This process would prevent any ability to select an accommodation based on the race of the host. However, staying with another individual is much more personal than riding in another person's car, so making these changes might bring harm to Airbnb's business.

Another option would be to eliminate the rather personal aspect of the listings. This could mean that hosts are not allowed to use their real names or personal photos as a supplement to their listings. While this change removes the personal aspect to the model and may decrease trust, a factor proven important in other studies, it would prevent guests from discovering any personal characteristics of the hosts, thus preventing them from discriminating based on ethnicity. Other online services that facilitate the transaction of goods and services between consumers use similar models, in that sellers and buyers do not need to disclose personal information. For example, EBay does so, while not dissuading users from buying goods on their website. Instead of seeing a photograph of the seller, buyers form trust based upon previous ratings of the seller. This model would likely work for Airbnb, and they may want to consider trying it out.

This study demonstrates the presence of racial discrimination on Airbnb, a sharing economy platform that connects hosts with guests searching for travel accommodations. My results parallel those of past studies that found that minority hosts charge less than White hosts for listings with similar characteristics, while expanding on these results and finding that White hosts also achieve higher annual occupancy rates than non-White hosts, despite charging higher prices. In the future, Airbnb consider changing their business model, in an effort to prevent racial discrimination and to provide equal opportunities for all users.

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Table 1: Variables and Descriptive Statistics

Variable	Description	Mean	St. Dev.	Min.	Max.
AC	Dummy variable: 1 if the Airbnb has air conditioning, 0 if it does not	0.856	0.3514413	0	1
Average Daily Rate	The average daily price of the Airbnb from 10/11/15 to 10/11/16	128.8335	101.6279	24.1	1543.08
Bathrooms	Total number of bathrooms included in each Airbnb	1.067	0.2648609	0.5	3.5
Bedrooms	Total number of bedrooms included in each Airbnb	1.102204	0.5699778	0	5
Breakfast	Dummy variable: 1 if the Airbnb includes breakfast, 0 if it does not	0.072	0.2587468	0	1
Buzzer	Dummy variable: 1 if the Airbnb has a buzzer at the door, 0 if it does not	0.578	0.4943731	0	1
CableTV	Dummy variable: 1 if the Airbnb includes cable television, 0 if it does not	0.306	0.4612912	0	1
Cancellation1	Dummy variable: 1 if the host has a "flexible" cancellation policy, 0 if the host does not	0.19	0.3926938	0	1
Cancellation2	Dummy variable: 1 If the host has a "moderate" cancellation policy, 0 if the host does not	0.28	0.4494486	0	1
Cancellation3	Dummy variable: 1 if the host has a "strict" cancellation policy, 0 if he does not	0.53	0.499599	0	1
CleaningFee	The total cleaning fee added to the price of an Airbnb	40.908	37.45752	0	200
CreatedDate	The date that the host created the Airbnb listing	6/12/14	3/3/01	11/25/09	10/8/15
Doorman	Dummy variable: 1 if the Airbnb has a doorman at the entrance, 0 if it does not	0.046	0.2096949	0	1
Dryer	Dummy variable: 1 if the Airbnb has a dryer, 0 if it does not	0.306	0.4612912	0	1
Elevator	Dummy variable: 1 if the Airbnb has an elevator, 0 if it does not	0.334	0.472112	0	1
Essentials	Dummy variable: 1 if the Airbnb includes "essentials" such as bed sheets and towels, 0 if it does not	0.836	0.3706464	0	1
ExtraPeopleFee	The total additional fee for each extra guest	15.138	18.53327	0	120
FamilyFriendly	Dummy variable: 1 if the Airbnb is suitable for families, 0 if it is not	0.392	0.4886856	0	1
FreeParking	Dummy variable: 1 if the Airbnb includes free parking, 0 if it does not	0.094	0.292121	0	1
Gym	Dummy variable: 1 if the Airbnb includes gym access, 0 if it does not	0.052	0.2222494	0	1
Hairdryer	Dummy variable: 1 if the Airbnb includes a hairdryer, 0 if it does not	0.356	0.4792947	0	1
Hangers	Dummy variable: 1 if the Airbnb includes hangers, 0 if it does not	0.38	0.4858726	0	1
Heating	Dummy variable: 1 if the Airbnb has heating, 0 if it does not	0.97	0.1707581	0	1
Hottub	Dummy variable: 1 if the Airbnb includes a hot tub, 0 if it does not	0.052	0.2222494	0	1
HrCheckin	Dummy variable: 1 if the host allows 24-hour check-in, 0 if the host does not	0.206	0.4048355	0	1
IndoorFireplace	Dummy variable: 1 if the Airbnb has an indoor fireplace, 0 if it does not	0.032	0.1761763	0	1
Instabook	Dummy variable: 1 if the host allows instant booking, 0 if the host does not	0.122	0.3276136	0	1

Internet	Dummy variable: 1 if the Airbnb provides internet access, 0 if it does not	0.842	0.3651063	0	1
Iron	Dummy variable: 1 if the Airbnb provides an iron, 0 if it does not	0.354	0.4786881	0	1
Kitchen	Dummy variable: 1 if the Airbnb includes a kitchen, 0 if it does not	0.96	0.1961554	0	1
Price	The average price of an Airbnb from 10/11/15 to 10/11/16	0.304	0.4604433	0	1
LaptopFriendly	Dummy variable: 1 if the Airbnb includes a laptop friendly workspace, 0 if it does not	0.458	0.4987319	0	1
ListingTypes1	Dummy variable: 1 if the Airbnb is a full home or apartment, 0 if it is not	0.52	0.5001002	0	1
ListingTypes2	Dummy variable: 1 if the Airbnb is a private room in the host's home, 0 if it is not	0.022	0.1468302	0	1
ListingTypes3	Dummy variable: 1 if the Airbnb is a shared room with other guests, 0 if it is not	2.676	1.579878	1	16
lbathroomssq	The log of the number of bathrooms allowed provided in an Airbnb squared	0.03948	0.15357	0	1.088136
lmaxguests	The log of the maximum number of guests allowed at the Airbnb	0.36882	0.221071	0	1.20412
lprice	The log of the average daily price of an Airbnb from 10/11/15 to 10/11/16	2.03748	0.235525	1.38202	3.1884
MaxGuests	The maximum number of guests allowed at the Airbnb	3.13	3.55223	1	30
MinimumStay	The minimum number of nights a guest must book at the Airbnb	0.234	0.4237962	0	1
Neighborhoods1	Dummy variable: 1 if the Airbnb is in Astoria, New York City, 0 if it is not	0.204	0.4033726	0	1
Neighborhoods2	Dummy variable: 1 if the Airbnb is in Flatbush, New York City, 0 if it is not	0.364	0.4816305	0	1
Neighborhoods3	Dummy variable: 1 if the Airbnb is in the Lower East Side, New York City, 0 if it is not	0.022	0.1468302	0	1
Neighborhoods4	Dummy variable: 1 if the Airbnb is in Richmond Hill, New York City, 0 if it is not	0.176	0.3812016	0	1
Neighborhoods5	Dummy variable: 1 if the Airbnb is in Washington Heights, New York City, 0 if it is not	16.096	10.65598	1	99
NumberofPhotos	The total number of photos provided of the Airbnb	27.242	32.69822	0	196
NumberofReviews	The total number of reviews posted to the Airbnb listing by prior guests	0.635516	0.2471743	0.036	1
OccupancyRateLTM	The occupancy rate of an Airbnb from 10/11/15 to 10/11/16	4.629079	0.3937291	0	5
OverallRating	The average rating of an Airbnb from prior guests, ranging from 0-5.	0.14	0.3473345	0	1
Pets	Dummy variable: 1 if guests are allowed to bring pets, 0 if they are not	0.004	0.0631821	0	1
Pool	Dummy variable: 1 if the Airbnb includes access to a pool, 0 if it does not	0.89	0.3132031	0	1
Price	The average price of the Airbnb from 10/11/15 to 10/11/16	0.006	0.0773043	0	1
PropertyTypes1	Dummy variable: 1 if the Airbnb is an apartment, 0 if it is not	0.004	0.0631821	0	1
PropertyTypes2	Dummy variable: 1 if the Airbnb is a bed & breakfast, 0 if it is not	0.006	0.0773043	0	1
PropertyTypes3	Dummy variable: 1 if the Airbnb is a condominium, 0 if it is not	0.088	0.2835786	0	1
PropertyTypes4	Dummy variable: 1 if the Airbnb is a dormitory, 0 if it is not	0.004	0.0631821	0	1

PropertyTypes5	Dummy variable: 1 if the Airbnb is a house, 0 if it is not	0.002	0.0447214	0	1
PropertyTypes6	Dummy variable: 1 if the Airbnb is a loft, 0 if it is not	91.814	16.2716	14	100
PropertyTypes7	Dummy variable: 1 if the Airbnb is a townhouse, 0 if it is not	173.2385	315.0338	0	5100
ResponseRate	The number of inquiries to which the host responds divided by the total number of inquiries a host has received over the previous 90 days	0.624	0.4848651	0	1
SecurityDeposit	The dollar amount of the security deposit for the Airbnb	0.062	0.2413971	0	1
Shampoo	Dummy variable: 1 if the Airbnb includes shampoo, 0 if it does not	0.038	0.1913877	0	1
Smoking	Dummy variable: 1 if smoking is allowed at the Airbnb, 0 if it is not	0.078	0.2684402	0	1
Suitableforevents	Dummy variable: 1 if the Airbnb is "suitable for events," 0 if it is not	0.63	0.4832878	0	1
Superhost	Dummy variable: 1 if the host has received the "Superhost" designation, 0 if the host has not	0.296	0.4569481	0	1
Sqrtlbedrooms	The square root of the log of the number of bedrooms included in an Airbnb	0.0767	0.1990167	0	0.8360
TV	Dummy variable: 1 if the Airbnb includes a television, 0 if it does not	0.652	0.4768131	0	1
Washer	Dummy variable: 1 if the Airbnb includes a washing machine, 0 if it does not	0.1	0.3003005	0	1
White	Dummy variable: 1 if the host is White, 0 if the host is not White	0.988	0.1089943	0	1
Whitesq	The square of the dummy variable White	0.652	0.4768813	0	1
Wheelchair	Dummy variable: 1 if the Airbnb is wheelchair accessible, 0 if it is not	0.856	0.3514413	0	1
WirelessInternet	Dummy variable: 1 if the Airbnb includes wireless internet, 0 if it does not	128.8335	101.6279	24.1	1543.08

Table 2: Regression 1 Results

Number of Observations = 470
F(4, 465) = 74.91
Prob > F = 0.0000
R-squared = 0.3809
Root MSE = .43658
Robust Standard Errors

lprice	Coefficient	Std. Err.	t	P>t
whitesq	0.1753153***	.0427862	4.10	0.000
sqrtlbedrooms	0.3587079***	.0865192	4.15	0.000
lmaxguests	0.4807895***	.0447552	10.07	0.000
lbathroomssq	0.0031443	.0921143	0.03	0.973
_cons	4.119954	.0422559	97.50	0.000

Note: * significant at the 90% level, ** significant at the 95% level, * significant at the 99% level**

Table 3: Regression 2 Results

Number of Observations = 447
F(57, 386) = .
Prob > F = .
Adjusted R-squared = 0.7977
Root MSE= .26883
Robust Standard Errors

lprice	Coefficient	Std. Err.	t	P>t
sqrtlbedrooms	0.1660012***	0.0635855	2.61	0.009
whitesq	0.0721294**	0.0299435	2.41	0.016
lmaxguests	0.190249***	0.0478705	3.97	0.000
lbathroomssq	0.0582455	0.0679163	0.86	0.392
CreatedDate	-2.21E-06	0.0000374	-0.06	0.953
OverallRating	0.0712279	0.0740973	0.96	0.337
NumberofReviews	0.000333	0.0005241	0.64	0.526
ResponseRate	-0.0000229	0.0010381	-0.02	0.982
Superhost	0.0898668**	0.0411302	2.18	0.029
SecurityDeposit	0.0000653*	0.0000387	1.69	0.092
CleaningFee	0.0026696***	0.0006666	4.01	0.000
ExtraPeopleFee	-0.0006184	0.0008280	-0.75	0.456
MinimumStay	-0.0109962**	0.0043712	-2.52	0.012
NumberofPhotos	0.0026572*	0.0013795	1.93	0.055
Instabook	-0.0137508	0.0457631	-0.30	0.764
FreeParking	0.0690423	0.0520035	1.33	0.185
Elevator	0.0104089	0.0384327	0.27	0.787
Pets	-0.0018538	0.0386944	-0.05	0.962
HrCheckin	-0.0445659	0.0423429	-1.05	0.293
FamilyFriendly	0.0010413	0.0308112	0.03	0.973
Pool	0.0213059	0.0982134	0.22	0.828
Smoking	-0.0762254	0.0516540	-1.48	0.141
Doorman	-0.040813	0.0951179	-0.43	0.668
Suitableforevents	-0.0929348	0.1033079	-0.90	0.369
IndoorFireplace	0.1459704	0.0782027	1.87	0.063
Internet	-0.0414998	0.0378471	-1.10	0.274
Gym	-0.0083661	0.0708641	-0.12	0.906
Wheelchair	0.0200083	0.0634835	0.32	0.753
Hottub	-0.0524646	0.0705936	-0.74	0.458
WirelessInternet	-0.0067984	0.1560492	-0.04	0.965
Breakfast	0.0931998*	0.0557705	1.67	0.096
Kitchen	0.060665	0.0631370	0.96	0.337
CableTV	0.0034431	0.0344275	0.10	0.920
Washer	0.032116	0.0714568	0.45	0.653
Dryer	0.04351	0.0647359	0.67	0.502
Buzzer	0.0526532*	0.0318114	1.66	0.099
LaptopFriendly	-0.0887982**	0.0358772	-2.48	0.014
Iron	0.0141743	0.0496154	0.29	0.775
Hangers	-0.0245032	0.0435862	-0.56	0.574
Hairdryer	0.1021702**	0.0447363	2.28	0.023
TV	0.0270894	0.0311907	0.87	0.386
Shampoo	-0.0304651	0.0291427	-1.05	0.297
Heating	0.0036411	0.0622646	0.06	0.953

Essentials	-0.018035	0.0401323	-0.45	0.653
AC	0.054087	0.0445106	1.22	0.225
Neighborhoods1	0.0151148	0.0452817	0.33	0.739
Neighborhoods2	-0.0943219*	0.0487489	-1.93	0.054
Neighborhoods3	0.4598467***	0.0463220	9.93	0.000
Neighborhoods4	-0.2715038***	0.0888608	-3.06	0.002
Neighborhoods5	0	(omitted)		
PropertyTypes1	0.0216445	0.1611276	0.13	0.893
PropertyTypes2	0.3253909	0.2726965	1.19	0.234
PropertyTypes3	0.4575143**	0.1820777	2.51	0.012
PropertyTypes4	0.2233346	0.2060400	1.08	0.279
PropertyTypes5	0.1668243	0.1643677	1.01	0.311
PropertyTypes6	-0.1250697	0.2439265	-0.51	0.608
PropertyTypes7	0	(omitted)		
ListingTypes1	0.8485903***	0.1636225	5.19	0.000
ListingTypes2	0.4853332***	0.1601328	3.03	0.003
ListingTypes3	0	(omitted)		
Cancellation1	0	(omitted)		
Cancellation2	0.0256855	0.0439927	0.58	0.560
Cancellation3	-0.0415636	0.0421705	-0.99	0.325
OccupancyRateLTM	-0.45155***	0.0713997	−6.32	0.000
_cons	3.410005	0.8803448	3.87	0.000

Note: * significant at the 90% level, ** significant at the 95% level, * significant at the 99% level**

Table 4: Regression 3 Results

Number of Observations = 476
F(59, 415) = .
Prob > F = .
R-squared = 0.4122
Root MSE = .19957
Robust Standard Errors

OccupancyRateLTM	Coefficient	Std. Err.	t	P>t
White	0.0618387***	0.0217837	2.84	0.005
lprice	-0.2516029***	0.0370762	-6.79	0.000
NumberofReviews	0.0021339***	0.0003182	6.71	0.000
OverallRating	0.0743796**	0.0363795	2.04	0.042
ResponseRate	0.0017376**	0.0007721	2.25	0.025
ExtraPeopleFee	-0.0018951***	0.0005961	-3.18	0.002
SuitableforEvents	-0.1392748***	0.0468862	-2.97	0.003
Pool	0.2162540***	0.0000264	3.31	0.001
CreatedDate	0.0000534**	0.0239572	2.02	0.044
Bedrooms	-0.0025425	0.0405137	-0.11	0.916
Bathrooms	-0.0290420	0.0103641	-0.72	0.474
MaxGuests	0.0141761	0.03069	1.37	0.172
Superhost	0.0441316	0.0000213	1.44	0.151
SecurityDeposit	-0.0000327	0.0003456	-1.54	0.125
CleaningFee	-0.0001899	0.0030049	-0.55	0.583
MinimumStay	0.0049709*	0.0010495	1.65	0.099
NumberofPhotos	0.0013867	0.0306306	1.32	0.187
Instabook	0.0525373*	0.0361259	1.72	0.087
FreeParking	0.0504001	0.0298505	1.40	0.164
Elevator	-0.0010705	0.0270051	-0.04	0.971
Pets	0.0127740	0.0275758	0.47	0.636
HrCheckin	-0.0118998	0.0228091	-0.43	0.666
FamilyFriendly	0.0363236	0.0653363	1.59	0.112
Smoking	-0.0363339	0.0426808	-0.85	0.395
Doorman	0.0185117	0.0607494	0.30	0.761
IndoorFireplace	0.0503135	0.0484945	1.04	0.300
Internet	-0.0306410	0.0279809	-1.10	0.274
Gym	-0.0487219	0.0440342	-1.11	0.269
Wheelchair	-0.0049135	0.040974	-0.12	0.905
Hottub	-0.0304625	0.0451992	-0.67	0.501
WirelessInternet	-0.1111960*	0.0630494	-1.76	0.079
Breakfast	-0.0459260	0.0409681	-1.12	0.263
Kitchen	0.0021736	0.0378896	0.06	0.954
CableTV	-0.0374389	0.0240806	-1.55	0.121
Washer	0.0529492	0.0622736	0.85	0.396
Dryer	-0.0502666	0.0608939	-0.83	0.410
Buzzer	0.0207326	0.021956	0.94	0.346
LaptopFriendly	-0.0230708	0.0280177	-0.82	0.411
Iron	0.0214086	0.0322824	0.66	0.508
Hangers	-0.0013173	0.0348333	-0.04	0.970
Hairdryer	0.0319555	0.0313063	1.02	0.308
TV	-0.0004158	0.0236107	-0.02	0.986
Shampoo	-0.0187335	0.0241307	-0.78	0.438

Heating	0.0752769	0.0478945	1.57	0.117
Essentials	0.0145394	0.0286715	0.51	0.612
AC	-0.0496289	0.0358701	-1.38	0.167
Cancellation1	-0.0088888	0.0313522	-0.28	0.777
Cancellation2	0.0000000	(omitted)		
Cancellation3	0.0267752	0.0234947	1.14	0.255
ListingTypes1	0.0000000	(omitted)		
ListingTypes2	-0.1558193***	0.0326767	-4.77	0.000
ListingTypes3	-0.4271564***	0.07026	-6.08	0.000
Neighborhood1	0.0779865	0.0496236	1.57	0.117
Neighborhood2	0.0247207	0.0475378	0.52	0.603
Neighborhood3	0.2194368***	0.0531971	4.12	0.000
Neighborhood4	0.0000000	(omitted)		
Neighborhood5	0.0736422	0.0540235	1.36	0.174
PropertyType1	0.1218878	0.0843123	1.45	0.149
PropertyType2	0.0965289	0.1362807	0.71	0.479
PropertyType3	0.0732657	0.1982541	0.37	0.712
PropertyType4	0.0000000	(omitted)		
PropertyType5	0.1610076**	0.0786131	2.05	0.041
PropertyType6	0.1484190	0.109751	1.35	0.177
PropertyType7	0.2427222*	0.133904	1.81	0.071
_cons	0.0677254	0.5619453	0.12	0.904

Note: * significant at the 90% level, ** significant at the 95% level, * significant at the 99% level**

Table 5: Variable Groups and F-Test Results

Base Amenities	Luxury Amenities
F(18, 415) = 0.89, p = 0.5928	F(12, 415) = 2.71, p = 0.0015
AC	Breakfast
Buzzer	Doorman
CableTV	Elevator
Dryer	FreeParking
Essentials	Gym
Hairdryer	Hottub
Hanger	HrCheckin
Heating	IndoorFireplace
Internet	Pets
Iron	Pool
Kitchen	Suitableforevents
LaptopFriendly	WirelessInternet
Shampoo	
Smoking	
TV	
Washer	
Wheelchair	

Listing Characteristics	Property Characteristics
F(12, 415) = 16.72, p = 0.0000	F(12, 415) = 6.53, p = 0.0000
Bathrooms	ListingTypes1
Bedrooms	ListingTypes2
CleaningFee	ListingTypes3
Instabook	Neighborhoods1
ExtraPeopleFee	Neighborhoods2
MaxGuests	Neighborhoods3
MinimumStay	Neighborhoods4
NumberofPhotos	Neighborhoods5
NumberofReviews	PropertyTypes1
OverallRating	PropertyTypes2
SecurityDeposit	PropertyTypes3
	PropertyTypes4
	PropertyTypes5
	PropertyTypes6
	PropertyTypes7

Host Characteristics
F(6, 415) = 3.64, p = 0.0015
Cancellation1
Cancellation2
Cancellation3
ResponseRate
Superhost
White