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Three Essays on Sharing Economy

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THREE ESSAYS ON SHARING ECONOMY

by

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ABSTRACT

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Under Supervision of Professor Purushottam Papatla

Overview

The sharing economy for services like Uber and Airbnb has grown significantly. The growth is driven by technology that "whittled down the barriers to the formation and functioning of sharing markets by lowering or eliminating frictions in the identification, search, match, verification, and exchange" (Narasimhan et al 2017).

Reductions in friction in steps to consummate transactions offer two types of savings to consumers. One, *monetary savings*, results from lower prices typically offered by sharing economy providers (SEP's) relative to legacy providers (LP's). The second type of savings results from the reduced effort and/or time that consumers need to search, identify, and transact with providers. Thus, a consumer does not have to wait for a taxi to pass by and can instead hail a ride on Uber. A traveler can find an accommodation at a preferred spot in a city easily even in the absence of traditional hotels at that spot. Such reductions in the time and/ or effort needed to locate desired services result in what we label as *hassle savings*.

While they may not be able to compete on monetary savings, LP's can still provide hassle savings. For instance, although they may cost more, by being more readily available, traditional cabs in a city like New York can help riders save the time to hail and wait for Uber. Whether consumers weigh monetary or hassle savings more may, however, vary with the consumption

context. For instance, avoiding the wait time for an Uber ride by taking a passing by taxi may weigh more if the ride is short and the savings are not substantial. The opposite may be true, however, for long rides where the difference in the cost of Uber and traditional taxis could be quite large. Monetary and/or hassle savings can, therefore, be strategic variables for LP's and SEP's. I examine if this is the case empirically in my dissertation through three essays on the sharing economy.

Essay 1: Monetary and Hassle Savings as Strategic Variables in the Ride-Sharing Market

The setting for my first essay is the ride-sharing market where I examine consumers' choices between Yellow Taxi and Uber in New York City. Specifically, I assume that consumers will weigh monetary savings less than hassle savings if the former is below a threshold but that the opposite will be true for larger savings. I investigate if this is the case using data on paid rides on Yellow Taxi and Uber in New York City. The period of my investigation lies between April 1, 2014 and September 30, 2014, during which data on all rides taken on Yellow Taxi's and Uber is available from the city.

I focus my investigation on the hundred most frequently occurring latitude, longitude, combinations from where rides on Yellow Taxis originate in the city. I then relate the odds of riders in these neighborhoods choosing Uber over Yellow Taxi for a ride on different days of the week and at different times of the day to my primary variable of interest - the availability of Yellow Taxis. I operationalize availability as a one-week lagged proportion of the total of rides on Yellow Taxis from the neighborhood to the total rides on Yellow Taxi in NYC. I also consider other factors like the intrinsic preference for Uber in that neighborhood and in New York City as a whole, weather, time of day, and type of neighborhood.

If my assumption about the relative importance of monetary and hassle savings is valid, there should be a ride distance below which Yellow Taxis should be preferred for the hassle savings and above which Uber should be preferred for the monetary savings. I find this indeed to be the case at a threshold of 6.64 miles.

Given the potential endogeneity of availability of Yellow Taxis, I take two approaches to assess the reliability of my finding. First, I assume that the availability of Yellow Taxis in each neighborhood could be endogenous with the demand for and availability of paid transportation in the neighborhood. Specifically, I recalibrate my model including two additional covariates as proxies for demand and availability of paid transportation: number of rides taken on subways closest to the neighborhood at the time of the ride and the distance to the nearest subway station. Two, I jointly estimate a supply side equation for the availability of Yellow Taxis in the neighborhood at the time of the ride as a function of a 1-week lagged availability of Yellow Taxis in the same neighborhood at the time of the ride and the demand for and availability of public transportation. I include the residual from this equation as an additional covariate in the log-odds model. Findings from both models are very similar to and consistent with those from the proposed model and confirm that there is a threshold distance below (above) which Yellow Taxis (Uber) is the preferred option.

Essay 2: Variations in the Strategic Value of Hassle Savings

The accommodation sharing market is the setting for my second and third essays. Accommodations are experience goods because amenities and the quality of services may vary from provider to provider, increasing consumers' uncertainty. Consumers, therefore, seek information on the features of accommodations before choosing one. Standardization mostly provides this information in the case of legacy providers like branded hotels. Sharing economy providers, however, cannot rely on standardization since the rented personal accommodations do vary across providers. Consumers, therefore, need to rely on alternative sources of information like user-generated ratings and reviews. Ratings and Reviews thus provide hassle savings by reducing uncertainty and can, therefore, be a strategic variable in the accommodation market. I investigate its effect in my second essay.

In the first essay, I examined variations in the relative value of monetary and hassle savings with consumption context. In this essay, I investigate whether the value of hassle savings itself varies with consumption context. If it does, the strategic role of features that provide hassle savings to sharing economy customers will also vary for providers. Providers should then invest more in features that provide hassle savings in contexts where they are valued more but can reduce such investments in other contexts.

Specifically, my goal is to understand if hosts obtain price premiums for receiving higher ratings from guests and how those premiums vary across consumption contexts, which I operationalize as different types of accommodations and regions within the city. Airbnb guests realize hassle savings by relying on ratings provided by other guests to reduce uncertainty about the features and services of listings. The value of the savings should, therefore, be higher in consumption contexts with greater uncertainty.

I hypothesize that uncertainty is likely to be higher under two consumptions contexts. One, where the number of listings in a location is very large. Two, where the number of listings and hence the number of ratings is small. I investigate if these are indeed the patterns by estimating a hedonic model of rental prices for Airbnb listings between April 2016 and October 2017 in the five boroughs of New York City for three types of accommodations: (1) entire – a house or apartment rented in its entirety (2) private – one room in an apartment and (c) shared – an accommodation shared by multiple guests. In each of the borough-type combinations, I assume that listings that receive an average rating of 5.0 are the treatment group and those with ratings of 4.0 – 4.99 are part of the control group. I then use propensity score matching to identify the treatment and control samples for each of the combinations. Estimates of the effect of a higher rating on the price premium are consistent with my hypotheses. Premiums are higher in combinations that have fewer listings or have a large number of listings.

Essay 3: Social Relationships as Strategic Variable in the Accommodation-Sharing Market

In addition to reviews and ratings (as in Essay 2), an additional source that sharing economy providers have been offering is information on whether the host or any previous buyers of a shared accommodation are acquaintances of a prospective renter. Airbnb, for instance, offers this through a feature called *social connections* that allows visitors to see only those accommodations reviewed by their friends or friends of friends on Facebook. The feature thus provides hassle savings by reducing uncertainty (perceived risk) and can, therefore, be a strategic variable in the accommodation market. I investigate its effect in my third essay.

My empirical analysis involves data on the search and time to the first purchase of a sharing accommodation by those who register on the Airbnb site. I examine two outcomes: (1) whether or not a purchase occurs (2) time to purchase if one occurs. The data includes Airbnb consumer prospects who registered between January 2014 and June 2014. I select consumer prospects who have used social connection feature at least once and use a proportional hazards model to relate time to first purchase to my primary variable of interest – social connections. I operationalize social connections as the number of times that a registered user uses the social connections feature before making the first purchase or terminating the search without a purchase. I also control for the effects of demographics (gender and age), how a registered user first arrived at the Airbnb site (e.g., via a link on Facebook or a search engine), and the number devices she uses for accessing the Airbnb site. I model the occurrence of the purchase/non-purchase of an accommodation as a binary logit related to the same variables and model the two outcomes jointly. My findings indicate a significant effect of social connections in reducing the time to, and increasing the likelihood of, the first purchase.

The social connections variable could, however, be endogenous with search time. Those who have friends on Facebook may be more experienced online users and hence, faster in searching and more willing to purchase, online. Additionally, they may be using the social connections feature only because it allows them to see which of their friends may be hosts or had used accommodations they are also considering. I take two approaches to investigate whether there are alternative explanations for my findings. First, I use propensity score matching with visitors who use the social connections feature on Airbnb as the treatment group matched with those who do not use this feature and re-estimate my models on the pooled sample. I use signup method which indicates whether people used Facebook/Google to set up an account on Airbnb before searching for accommodations. I also use age as a matching variable as a proxy for experience with- and interest in- using social media and learning about friends' activities. Results from this re-estimation are consistent with my findings and indicate that social connections are indeed reducing search time and increasing the likelihood of a purchase.

Second, I exploit possible geographic differences in the hassle savings' value of social connections to validate my findings. Specifically, I hypothesize that the value of hassle savings should be larger when someone is searching internationally rather than domestically in the US since uncertainty should be higher with the former. I therefore re-estimate my model with geographic-specific estimates of the effects of social connections. I do find that the effects are larger both on the time to make the first purchase and on the likelihood of the first purchase for international listings than domestic ones.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Essay 1: Monetary and Hassle Savings as Strategic Variables in the Ride-Sharing Market

1.1 Introduction

Sharing economy providers host digital platforms through which individuals can sell services to other individuals (Bardhi and Eckhardt 2012, Zervas et al 2014). Examples of these platforms include Airbnb for accommodation, Peerby for appliances and equipment, Eatfeastly for dining, and Uber for transportation. A recent survey by PwC (PwC 2015) suggests that about 44% of US consumers are aware of the sharing economy and 19% have engaged in at least one sharing economy transaction.

Due to the rising interest among consumers, the sharing economy has been growing rapidly. For example, Uber entered New York City in May 2011 and currently offers more than 46,000 cars far exceeding the 14,000 Yellow Taxis in the city (The New York Times 2017). Perhaps reflecting this, the average number of daily trips on Yellow Taxis fell by more than 132,000 trips – about 26% – in June 2016 from the same month in 2011 (TLC 2016). Similarly, Airbnb which had more than 50,000 listings in New York City in 2015 is estimated to have cost the NYC hotel industry $451 million in lost revenue during the twelve-month period ending in August 2015 (HVS 2015). As consumer interest in buying through sharing platforms continues to increase, the revenue of this segment of the economy is predicted to reach $335 billion by 2025 globally (PwC 2015).

The rapid growth of sharing economy is driven by technology that “whittled down the barriers to the formation and functioning of sharing markets by lowering or eliminating frictions in the identification, search, match, verification, and exchange” (Narasimhan et al 2017). These reductions in friction in steps to consummate transactions offer two types of savings to consumers.

One, *monetary savings*, results from lower prices typically offered by sharing economy providers (SEP's) relative to legacy providers (LP's). The second type of savings results from reduced effort and/or time that consumers need to search, identify, and transact with providers. Thus, a consumer does not have to wait for a taxi to pass by and can instead hail a ride on Uber. A traveler can find an accommodation at a preferred spot in a city easily even in the absence of traditional hotels at that spot. Such reductions in the time and/ or effort needed to locate desired services result in what we label as *hassle savings*.

While they may not be able to compete on *monetary savings*, LP's can still provide hassle savings. For instance, although they may cost more, by being more readily available, traditional cabs in a city like New York can help riders save the time to hail and wait for Uber. Whether consumers weigh monetary or hassle savings more may, however, vary with the consumption context. For instance, avoiding the wait time for an Uber ride by taking a passing by taxi may weigh more if the ride is short and the savings are not substantial. The opposite may be true however for long rides where the difference in the cost of Uber and traditional taxis could be quite large. Monetary and/or hassle savings can, therefore, be strategic variables for LP's and SEP's. we examine if this is the case empirically in this research.

The setting for this research is the ride-sharing market where we examine consumers' choices between Yellow Taxi and Uber in New York City. Specifically, we assume that consumers will weigh monetary savings less than hassle savings if the former is below a threshold but that the opposite will be true for larger savings.

We empirically test the above predictions in New York City. In particular, we investigate whether the differences in the pricing structures of Uber, the SEP, and Yellow Taxi, the LP, and the availability of Yellow Taxi in these markets affects consumer preferences for the two options based on the distance traveled on the ride. Data for our investigation comes from an individual investigator who compiled and made some of the data that we use publicly available for research (Schneider 2015) and the New York City Taxi and Limousine Commission (TLC 2017). This Commission maintains detailed records of every ride on Yellow Taxis in the city including variables like the origination and termination points of the trip, the trip cost, the start and end times, the number of passengers on the ride, and whether the fare was paid with cash or a credit card.

The specific neighborhoods that we investigate are the top one hundred most frequently occurring latitude, longitude, combinations from where rides on Yellow Taxis originate in New York City between April 1, 2014 and September 30, 2014, which is a period during which trip-level data on all rides provided by Uber in the city are also available. To infer availability of Yellow Taxis in each neighborhood, we take advantage of the fact that they have to be available and visible in the neighborhood to be hailed and use one-week lagged total Yellow Taxi rides as a proportion of all rides on Yellow Taxis in New York City as a proxy for their availability. Since we have the number of rides on Uber and Yellow Taxi, we take a log-odds approach to model the probability of a consumer in the neighborhood i during period p on day t choosing Uber over Yellow Taxi. The odds are assumed to be a function of the availability of Yellow Taxis in the neighborhood and several factors that can affect riders' preferences such as the intrinsic preference for Uber in that neighborhood and in New York City as a whole, weather, time of day, and type of neighborhood.

If our assumption about the relative importance of monetary and hassle savings is valid, there should be a ride distance below which Yellow Taxis should be preferred for the hassle savings and above which Uber should be preferred for the monetary savings. We find this indeed to be the case at a threshold of 6.64 miles.

Given the potential endogeneity of availability of Yellow Taxis, we take two approaches to assess the reliability of our finding. First, we assume that the availability of Yellow Taxis in each neighborhood could be endogenous with the demand for and availability of paid transportation in the neighborhood. Specifically, we recalibrate our model including two additional covariates as proxies for demand and availability of paid transportation: number of rides taken on subways closest to the neighborhood at the time of the ride and the distance to the nearest subway station. Two, we jointly estimate a supply side equation for the availability of Yellow Taxis in the neighborhood at the time of the ride as a function of a 1-week lagged availability of Yellow Taxis in the same neighborhood at the time of the ride and the demand for and availability of public transportation. We include the residual from this equation as an additional covariate in the log-odds model. Findings from both models are very similar to and consistent with those from the proposed model and confirm that there is a threshold distance below (above) which Yellow Taxis (Uber) is the preferred option.

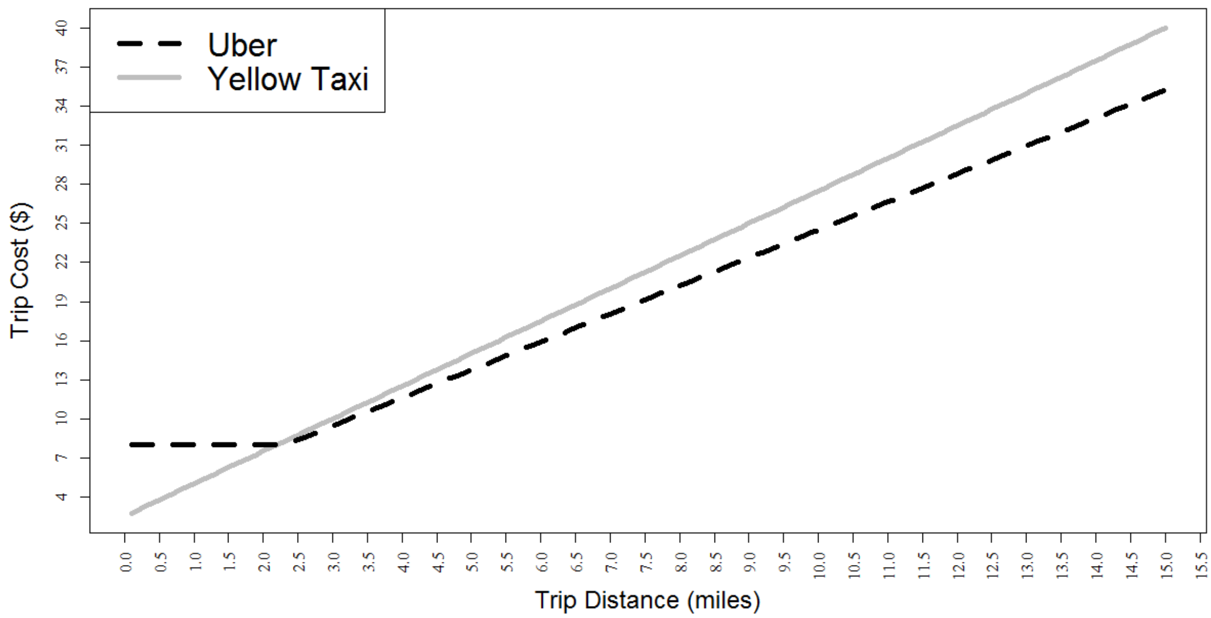
We next present relevant literature to our research and develop our framework. Then, we provide the description of our data. Following this, we present our models and discuss our empirical results. We conclude with a summary of our findings and directions for future research.

1.2 Background

The sharing economy for services like Uber and Airbnb has grown significantly. The growth is driven by technology that "whittled down the barriers to the formation and functioning of sharing markets by lowering or eliminating frictions in the identification, search, match, verification, and exchange" (Narasimhan et al 2017). Reductions in friction in steps to consummate transactions offer two types of savings to consumers. One, *monetary savings,* results from lower prices typically offered by sharing economy providers (SEP's) relative to legacy providers (LP's). The second type of savings results from the reduced effort and/or time that consumers need to search, identify, and transact with providers. Thus, a consumer does not have to wait for a taxi to pass by and can instead hail a ride on Uber. A traveler can find an accommodation at a preferred spot in a city easily even in the absence of traditional hotels at that spot. Such reductions in the time and/ or effort needed to locate desired services result in what we label as *hassle savings*. These savings can be notable and impact utility. We develop our theoretical framework based on the notion that hassle savings would increase the utility of transactions.

To motivate our research, we start by noting that SEP's offer the same core services as LP's. For instance, both Uber and taxis provide paid rides and Airbnb provides accommodations like hotels do. A key difference between SEP's and LP's, however, is in their pricing structures, which provides monetary savings (Figure 1.1) based on the ride distance. For instance, Yellow Taxis in New York City use a two-part tariff that includes an initial charge of $2.50 for a ride plus $2.50 per each mile traveled and 50 cents per minute of idle time. Uber also uses a two-part tariff but had a different schedule (during the period of our study) that included a base fare of $2.55 for a ride, $1.75 per each mile traveled and 35 cents per minute of idle time. Uber also sets the minimum fare to $8 which is the minimum that riders need to pay for any ride (TLC 2017, NYC Post 2017). Thus, if consumer preferences were based solely on monetary savings, taxi-cabs should be preferred over Uber for rides that are shorter than or equal to a trip distance, d^*, where the costs of rides on both the options are equal.

Figure 1.1: Trip Distance and Trip Cost on Uber and Yellow Taxi



The second difference between SEP's and LP's is in the secondary attributes (Keller 2003, Kotler and Armstrong 2004, Rust, Zahorik and Keiningham 1996) of their services that can enhance or detract from the consumption experience by providing hassle savings. For instance, in some neighborhoods, on some days of the week and some periods of the day (e.g., morning and evening rush hours), taxi-cabs may be more easily available if cab drivers find the neighborhoods more attractive (Lagos 2000) due to a higher likelihood of finding customers there during those days and times. In this case, it would be faster for the consumer to use a traditional taxi-cab rather than requesting a ride on Uber through the app, waiting for an Uber driver to accept the request, and then for the driver to arrive to give her the ride. The average waiting time for Uber in 2014 was 3.2 minutes in New York City (Uber 2017). However, this could take a long time if, for instance, an Uber driver is not in the vicinity and has to arrive from a different area. The consumer would thus not incur any waiting costs (Antonides et al 2002, Osuna 1985) if she chooses a taxi-cab. In other cases, it may be faster for her to request a ride on Uber than to wait for an empty taxi-cab to pass by. She may then prefer Uber over a taxi-cab.

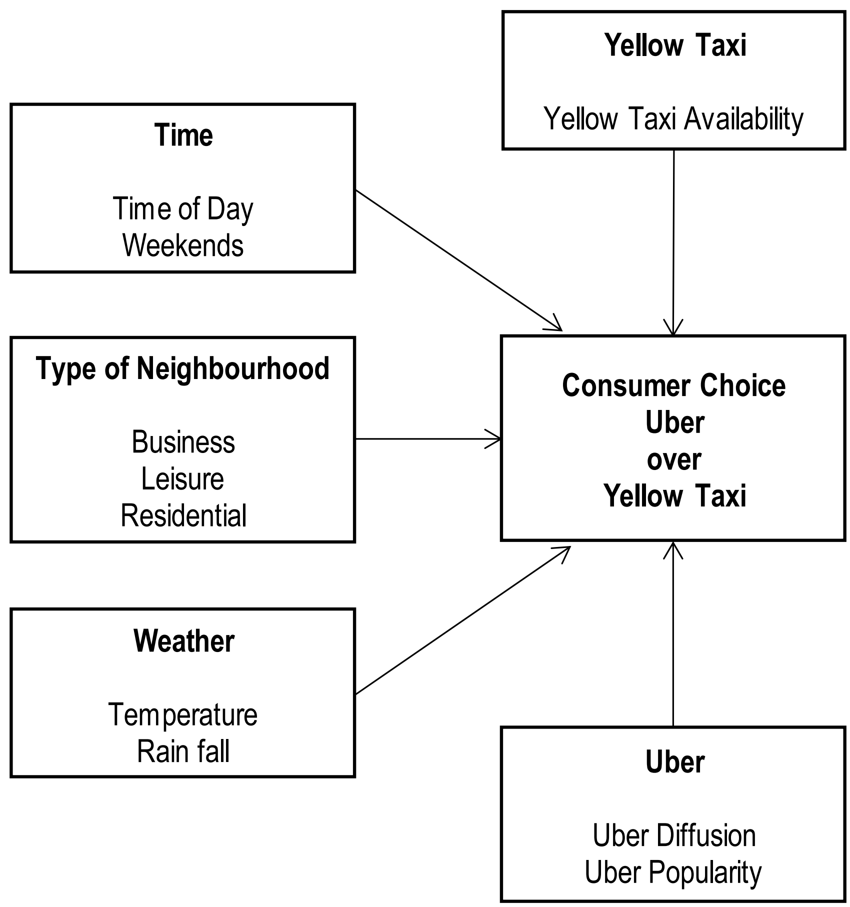
Both options would, therefore, have different customer-transaction costs which are "service-related costs" such as "search effort, ease or difficulty in getting problems resolved .. required to access or use the service" Oliva et al 1992, p.85). The differences in the pricing structures and differences in the availabilities of taxi-cabs and Uber may change the customer-transaction costs associated with each option and shift consumer preferences between the two. In other words, consumers' preferences between Uber and taxi-cabs switch based on the total transaction costs.

Overall, therefore, if taxi-cabs are readily available and consumers weigh hassle savings more than monetary savings, they may prefer a taxi-cab over Uber even for rides longer than d^* although the ride on Uber provides monetary savings. In other words, the consumer may prefer Yellow Taxi when she is taking trips that are below a threshold trip distance ($d^* + d^w$) where the total monetary savings by taking a ride on Uber are substantially lower than the total hassle savings by taking a ride on Yellow Taxi.

Above a threshold trip distance ($d^* + d^w$) where the total monetary savings by taking a ride on Uber start becoming substantially larger than the total hassle savings by taking a ride on Yellow Taxi, i.e., consumers start weighing monetary savings more than hassle savings, they may prefer waiting on average 3.2 minutes for Uber instead of taking ride on a taxi-cab that readily available.

The differences in the pricing structures and availability of taxi-cabs and Uber, therefore, may change the customer-transaction costs associated with each option and shift consumer preferences between the Yellow Taxi and Uber. Specifically, we assume that consumers will weigh monetary savings less than hassle savings if the former is below a threshold but that the opposite will be true for larger savings. Thus, our hypothesis is that: **Consumers will weigh monetary savings less (more) than hassle savings if the former is below (above) a threshold.** We further argue this could depend on the neighborhood, as the availability of Yellow taxi and/or Uber could vary by neighborhood. We thus hypothesize that **Consumers differently weigh monetary and hassle savings by neighborhood.**

Figure 1.2: Framework



We also include two variables related to weather conditions in the model. First, mean rain fall in New York City. Farber (2015) examines the rain effect on demand and supply for rides in NYC and finds that drivers are less likely to prefer to drive in the rain due to traffic conjunctions. Brodeur and Nield (2016) find an empirical evidence that Uber drivers positively respond to increasing demand when it rains. It is intuitive that consumers can wait in offices, homes, or wherever they are for Uber, instead of going out in the rain to find a Yellow Taxi. Second, the mean temperature which influences demand and supply for rides in NYC. It is very intuitive that people require more rides i.e., demand for rides increases when the temperature is cold. While, when the temperature getting warmer and hot, more and more people come to the NYC, including travelers, which increase the demand. We thus include these two variables to control for variation in demand and supply of rides due to weather.

1.3 Data

Data for our investigation comes from an individual investigator (Schneider 2015) who compiled and made publicly available some of the data that we use[1] and the New York City Taxi and Limousine Commission (TLC 2017). This Commission maintains detailed records of trip data for each Yellow Taxi ride including the origination and destination point (in terms of latitude and longitude of each), date of the trip, start and end times of the trip, the number of passengers, distance traveled, and the total cost of the trip. Schneider (2015) augmented this data with data on weather including temperature and rainfall in New York City for each date during April 1, 2014 to September 30, 2014, which is the period during which data on all rides taken on Uber in New York City is also available and is also our analysis period.

We consider all trips taken within the geographical boundaries of New York City which include the latitude and longitude coordinate set [40.477399, 40.917577] and [-74.259090, -

[1] The investigator's sources of data and approaches to compiling the data are described at http://toddwschneider.com/posts/analyzing-1-1-billion-nyc-taxi-and-uber-trips-with-a-vengeance/.

73.700272 (Hafen 2015, Li et al 2014)[2]. We exclude all the trips with travel distances less than 0.02 miles and with missing values for any of the variables included in the analysis. We first round the latitude and longitude to three digits and identify the top one hundred origination points (latitude and longitude pairs) based on the total number of rides at the origination point over the investigation period[3]. We subsequently refer to this set of points as neighborhoods. We next divide each day into two twelve-hour periods from 5 AM to 5 PM and 5:00 PM to 5:00 AM. We aggregate the rides during each period and obtain the total number of rides, the mean trip distance, and the mean number of passengers over each period of each day for each neighborhood. The Uber dataset also contains the latitude and longitude of the origination point, date of the trip, and start-time of the trip. We are therefore able to identify all the rides taken on Uber during each period of each date of the analysis period from the same hundred neighborhoods that we consider for Yellow Taxis.

Our final dataset thus includes a panel of 100 neighborhoods each of which is observed over the 183 days during the analysis period. Since we divide each day into two periods, the data includes 366 observations for each of the hundred neighborhoods for a total 36,600 observations. For each neighborhood, we use the first 14 observations to compute lagged variables as discussed shortly, the next 280 observations for model estimation and the remaining 72 observations for predictive testing of the models. The dataset, as a whole, therefore is divided into 1400 observations for computing the lagged variables, 28000 observations for model estimation, and

[2] The approach for setting NYC bounding box with coordinates is described at http://hafen.github.io/taxi/#reading-in-to-r .

[3] There were a total of 62,075 identifiable origination points in the data but the top 100 rides accounted for 15.6% of total rides during the investigation period.

7200 observations for predictive testing. We list below each variable that we compute from the data.

Y_{ipt} = all the rides taken on Yellow Taxis from neighborhood i during period p of day t.

U_{ipt} = all the rides taken on Uber from neighborhood i during period p of day t.

$OR_{ipt} = \left(\frac{U_{ipt}}{Y_{ipt}}\right)$ is the odds-ratio of an individual taking a ride on Uber rather than on Yellow Taxi from neighborhood i during period p of day t.

TD_{ipt} = mean trip-distance for rides on all Yellow Taxi from neighborhood i during period p on day t.

Day_p = indicator set to 1 for trips between 5 AM and 5 PM and 0 otherwise.

$WKEND_t$ = indicator set to 1 if the trip was taken during the weekend (Saturday or Sunday) and 0 otherwise.

Type of Neighborhood**:** We use neighborhood images provided by Google Maps to assign each of the 100 neighborhoods to one of four categories: airport, business, leisure or residential (Appendix 1). We define four corresponding indicator variables $Air_i, Leis_i, Res_i \; and \; Work_i$ one of which is set to 1 depending on the category to which *i* belongs and the others are set to zero.

$\overline{Rain}_t$ = average rainfall in inches in the New York City on day *t*.

$\overline{TEMP}_t$ = average temperature in New York City on day t.

P_{ipt} = Mean number of passengers per Yellow Taxi ride from neighborhood i during period p on day t.

$UCShr_{t-1}$ = 1-day lagged share of Uber in New York City. We compute $UCShr_t$ as the total number of rides on Uber in New York City on day t as a proportion of the total number of Uber and Yellow Taxi rides in New York City on day t. We use this variable as a proxy for consumer intrinsic preference for Uber in NYC.

$UNShr_{ip(t-7)}$ = 1-week lagged share of Uber in neighborhood i in all Uber rides in New York City. We compute $UNShr_{ipt}$ as the total number of rides on Uber in neighborhood i during period p on day t as the proportion of the total number of Uber rides in New York City during period p on day t. We use this variable as a proxy for consumer intrinsic preference for Uber in the neighborhood.

$YAvail_{ip(t-7)}$ = 1-week lagged share of Yellow Taxi in neighborhood i in all Yellow Taxi rides in New York City. This is our measure of the availability of Yellow Taxis in the neighborhood. We compute $YAvail_{ipt}$ as the total number of rides on Yellow Taxis in neighborhood i during period p on day t as the proportion of the total number of Yellow Taxi rides in New York City during period p on day t.

Table 1.1 presents descriptive summaries of all the variables.

Table 1.1: Descriptive Statistics

Continuous Variables				
Variable	**Mean**	**Standard Deviation**	**Min**	**Max**
Number of Uber Rides	10.564	13.193	0	235
Number of Yellow Rides	344.714	208.59	1	1734
Mean Trip Distance	3.57	3.236	1.3	16.6
Number of Public Rides	32935.055	30683.201	0	166674.39
Distance to Subway	0.174	0.137	0.01	0.7
Mean Temperature	69.04	8.918	39.5	86
Mean Rainfall	0.135	0.467	0	5.48
Mean Number of Passengers	1.707	0.113	1	2.42
Intrinsic Preference for Uber in NYC	0.03	0.025	0	0.26
Intrinsic Preference for Uber in Neighborhood	0.001	0.001	0.00	0.03
Availability of Yellow Taxis	0.002	0.001	0.00	0.01

Indicator Variables	
Variable	**Proportion**
Day (5 AM – 5 PM)	0.50
Weekend	0.28
Airport	0.12
Business	0.31
Leisure	0.25
Residential	0.32

1.4 Modeling Approach

We use Log-Odds approach to model consumer choice between Uber and Yellow Taxis. Specifically, we log-transform OR_{ipt} and regress on log-transformed versions of the continuous variables as well as the binary variables. We take two approaches, one segment-specific to test our primary hypothesis, and second location-specific to test our second hypothesis. Each approach is discussed next.

1.4.1 Segment-Specific Model

$$\ln(OR_{ipt}) \sim Normal\ (\mu_{OR_{ipt}}, 1) \tag{1}$$

$$\mu_{OR_{ipt}} = \sum_{j=1}^{2} \gamma_j . C_{ipt}^{j} . YAvail_{ip(t-7)} + \beta_0 + \beta_1 DAY_p + \beta_2 WKEND_t + \beta_3 Leis_i + \beta_4 Res_i + \beta_5 Work_i + \beta_6 \overline{TEMP}_t + \beta_7 \overline{Rain}_t + \beta_8 P_{ipt} + \beta_9 UCShr_{t-1} + \beta_{10} UNShr_{ip(t-7)} + \vartheta_{ipt} \tag{2}$$

$$C_{ipt}^{j} = \begin{Bmatrix} For\ j = 1; & 1\ if\ \ TD_{ipt} < LTD, & 0\ o/w \\ For\ j = 2; & 1\ if\ \ TD_{ipt} \geq LTD, & 0\ o/w \end{Bmatrix} \tag{3}$$

where C_{ipt}^{j} represents a latent segment, γ_j represent the effect of availability of Yellow Taxi and β represent the effect of other variables on the choice of Uber over Yellow Taxi, TD_{ipt} represents the observed trip distance, and LTD is represents the latent trip-distance. We assume that LTD is distributed uniformly over a range spanning a and b the smallest and largest observed trip-distances respectively in our data. The last term in the equation 2 ϑ_{ipt} is a random effect term to capture the unobserved heterogeneity. We assume that ϑ_{ipt} is distributed $Normal\ (0, \sigma_{\vartheta}^{2})$.

1.4.2 Location-Specific Model

To investigate whether neighborhoods are heterogeneous, we allow the effects of Yellow Taxis' availability to be neighborhood-specific and replace γ_j with γ_{ji} in equation 1.

$$\ln(OR_{ipt}) \sim Normal\ (\mu_{OR_{ipt}}, 1) \tag{4}$$

$$\mu_{OR_{ipt}} = \sum_{j=1}^{2} \gamma_{ij}. C_{ipt}^{j}. YAvail_{ip(t-7)} + \beta_0 + \beta_1 DAY_p + \beta_2 WKEND_t + \beta_3 Leis_i + \beta_4 Res_i + \beta_5 Work_i + \beta_6 \overline{TEMP}_t + \beta_7 \overline{Rain}_t + \beta_8 P_{ipt} + \beta_9 UCShr_{t-1} + \beta_{10} UNShr_{ip(t-7)} + \vartheta_{ipt} \quad (5)$$

$$C_{ipt}^{j} = \begin{Bmatrix} For\ j = 1; & 1\ if\ \ TD_{ipt} < LTD, \ \ 0\ o/w \\ For\ j = 2; & 1\ if\ \ TD_{ipt} \geq LTD, \ \ 0\ o/w \end{Bmatrix} \quad (6)$$

1.5 Model Estimation

We take a Bayesian approach and estimate the parameters of the model using MCMC methods available in JAGS (Plummer 2003). The prior distributions for the coefficients are proper but not-informative (Normal with mean zero and large variance), and for the precision term for the random term, Gamma distribution with mean one and large variance has been considered. We draw two chains of 25,000 samples each with random starting values for the parameters in the Markov chain. We discard the first 15,000 as burn-in and in the remaining samples; we select every 5th sample and retain 2,000 draws from each chain (total of 4000 draws) for posterior inference. We monitor the convergence of parameters graphically and using Gelman and Rubin's potential scale reduction factor. We use the value 1.1 or lower for monitoring convergence.

1.6 Results

We compare the segment-specific and location-specific model specifications based on their fit in terms of the Deviance Information Criterion (Gelman et al 2004) as well as on predictive performance using root mean squared error (RMSE) and mean squared error (MSE) in predictions. Model comparison results in Table 1.2 suggest that both the models are consistent in terms of model fit and predictive performance.

Table 1.2: Model Comparison

Model	DIC	RMSE	MSE
Segment Specific	72,095	0.765	0.586
Location Specific	69,501	0.764	0.584

Table 1.3: Convergence Statistics

Variable	Segment-Specific	Location-Specific
Constant	1.001	1.001
Day Time (5 AM to 5 PM)	1.001	1.001
Weekend	1.001	1.001
Business	1.001	1.002
Leisure	1.001	1.001
Residential	1.001	1.002
Mean Temperature	1.001	1.001
Mean Rainfall	1.001	1.001
Mean Number of Passengers	1.001	1.002
Intrinsic Preference for Uber in NYC	1.001	1.001
Intrinsic Preference for Uber in Neighborhood	1.001	1.001
Yellow Availability-Short Distance Segment	1.001	Figure 1.3
Yellow Availability-Long Distance Segment	1.001	Figure 1.4

Figure 1.3: Location Specific Model – Convergence Statistics for Segment 1

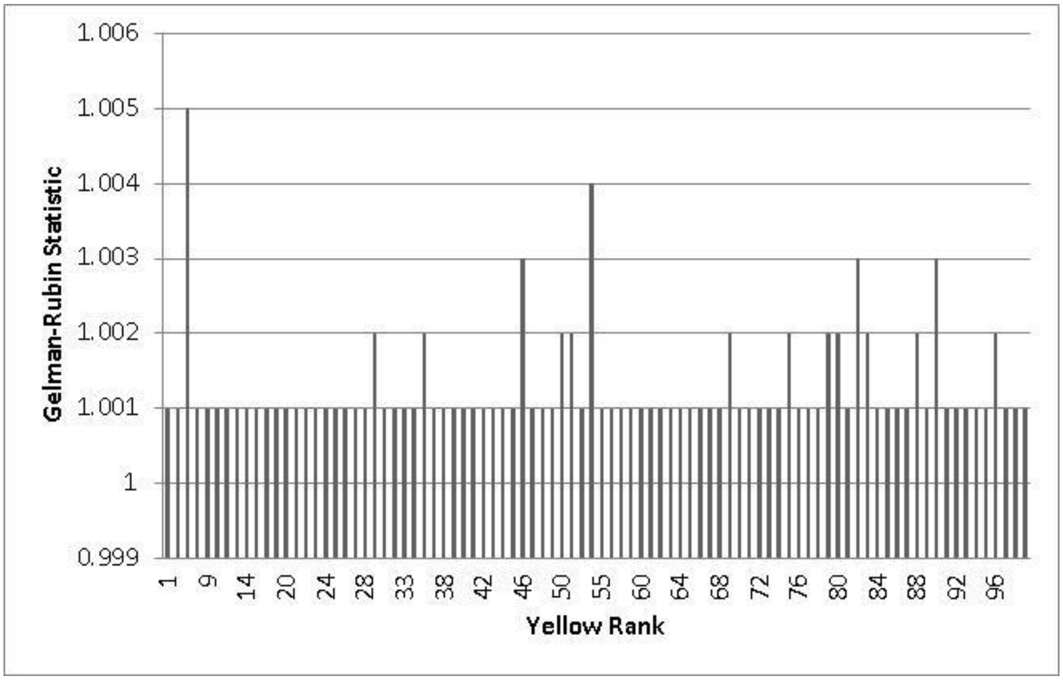
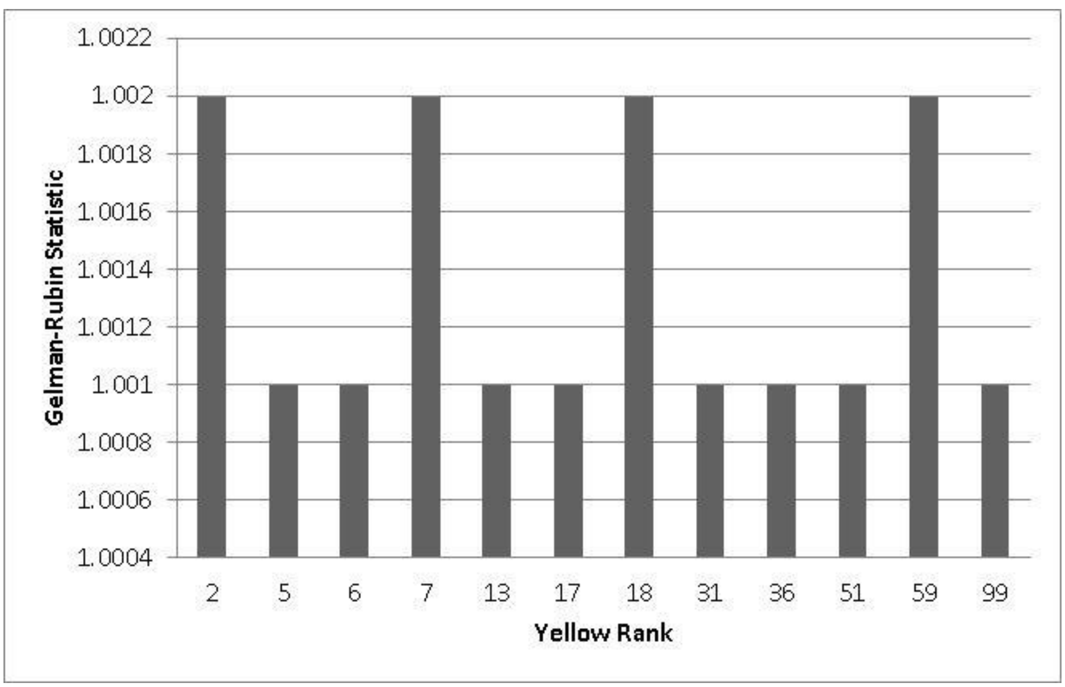


Figure 1.4: Location Specific Model – Convergence Statistics for Segment 2



We monitor convergence each parameter using Gelman Rubin statistics. Table 1.3 indicates that all parameters in both the models are converged, as each value is below 1.1. We next present the findings from both the models.

1.6.1 Results of segment-specific model

We estimate a latent threshold below which the effect of Yellow Taxi availability is different from that above. Estimates from the model presented in Table 1.4 are discussed next. As shown in the first column of Table 1.4, the results suggest that the threshold trip distance is about seven miles with a significant negative effect of the availability of Yellow Taxi on the odds of choosing Uber both below and above the threshold. Consistent with our prediction, however, the reduction in the odds of choosing Uber over Yellow Taxi is larger below (**-0.195**) the threshold than above (**-0.074**).

Estimated effects of other variables: The estimated effects of most of the other variables are significant and have intuitively meaningful signs. The coefficient for Day, for instance, is significant and positive. This is consistent with previous literature on the taxi market (Camerer et al. 1997, Farber 2005) that the supply of Yellow Taxis during the day in New York City is lower than the demand which should increase the preference for Uber. Not surprisingly, the coefficient for Weekend is negative and significant. This could be due to increased availability of Yellow Taxis during the weekend thus making them a preferred option relative to having to request and wait for an Uber driver. All three coefficients related to the type of neighborhood are significant and positively related to the odds of Uber over Yellow Taxi. Since the base neighborhood category in both models is Airport, this suggests that riders prefer Uber over Yellow Taxi for intracity rides. The airports are considered the best locations for yellow taxi drivers along with Manhattan's central business district where they can easily find customers. For taking a ride on Uber at an airport, consumers must go an allotted pick-up point with their luggage or wait for Uber to come, but they can easily find a Yellow Taxi outside of the relevant terminal.

Table 1.4: Estimated Parameters of Segment-Specific Model

Variable	**Mean**	**SD**
Constant	**-0.741**	0.021
Day Time (5 Am to 5 PM)	**0.136**	0.012
Weekend	**-0.281**	0.014
Business/Work	**0.816**	0.022
Leisure	**0.835**	0.023
Residential	**0.879**	0.023
Mean Temperature	0.012	0.007
Mean Rainfall	**0.029**	0.006
Mean Number of Passengers	**0.039**	0.007
Uber Popularity	**0.200**	0.007
Uber Diffusion	**0.455**	0.007
Availability of Yellow taxi in Segment 1	**-0.195**	0.008
Availability of Yellow taxi in Segment 2	**-0.074**	0.014
Threshold	6.64	
Segment 1	24640	
Segment 2	3360	
Total Number of Observations	28000	

Bold: 95% credible intervals exclude zero.

With respect to weather conditions, the estimate for mean temperature is positive but not significant. The estimate for precipitation is positive and significant suggesting an increase in mean rainfall increases the preference for Uber. This is consistent with anecdotal reports (Farber 2005) that it's difficult to find taxicabs in New York City during rainfall which should thus increase the preference for Uber. The coefficient of the mean number of passengers is positive and significant. We also find the popularity of Uber in the city and the diffusion of Uber in the neighborhood also increase the odds of Uber over Yellow Taxi.

1.6.2. Results from the location-specific model

Results from the location-specific model are displayed in Table 1.5.

Table 1.5: Estimated Parameters of Location-Specific Model

Variable	**Mean**	**SD**
Constant	**-0.672**	0.027
Day Time (5 Am to 5 PM)	**0.110**	0.014
Weekend	**-0.260**	0.015
Business/Work	**0.801**	0.031
Leisure	**0.792**	0.032
Residential	**0.873**	0.031
Mean Temperature	**0.021**	0.007
Mean Rainfall	**0.030**	0.006
Mean Number of Passengers	0.012	0.007
Uber Popularity	**0.198**	0.007
Uber Diffusion	**0.455**	0.010
Availability of Yellow taxi in Segment 1	Figure 1.5	
Availability of Yellow taxi in Segment 2	Figure 1.6	
Threshold	8.79	
Segment 1	88	
Segment 2	12	
Total Number of Locations	100	

Bold: 95% credible intervals exclude zero.

Consistent with our second hypothesis, the findings from these models indicate that the effect of availability of Yellow Taxies does vary across neighborhoods as shown in Figures 1.5 and Figure 1.6. The effect is also positive in some neighborhoods. Not surprisingly, these results could be attributed to the constant supply of Yellow Taxis in New York City which was unchanged for several years (Figure 1.8).

Figure 1.5: Location Specific Model – Segment 1

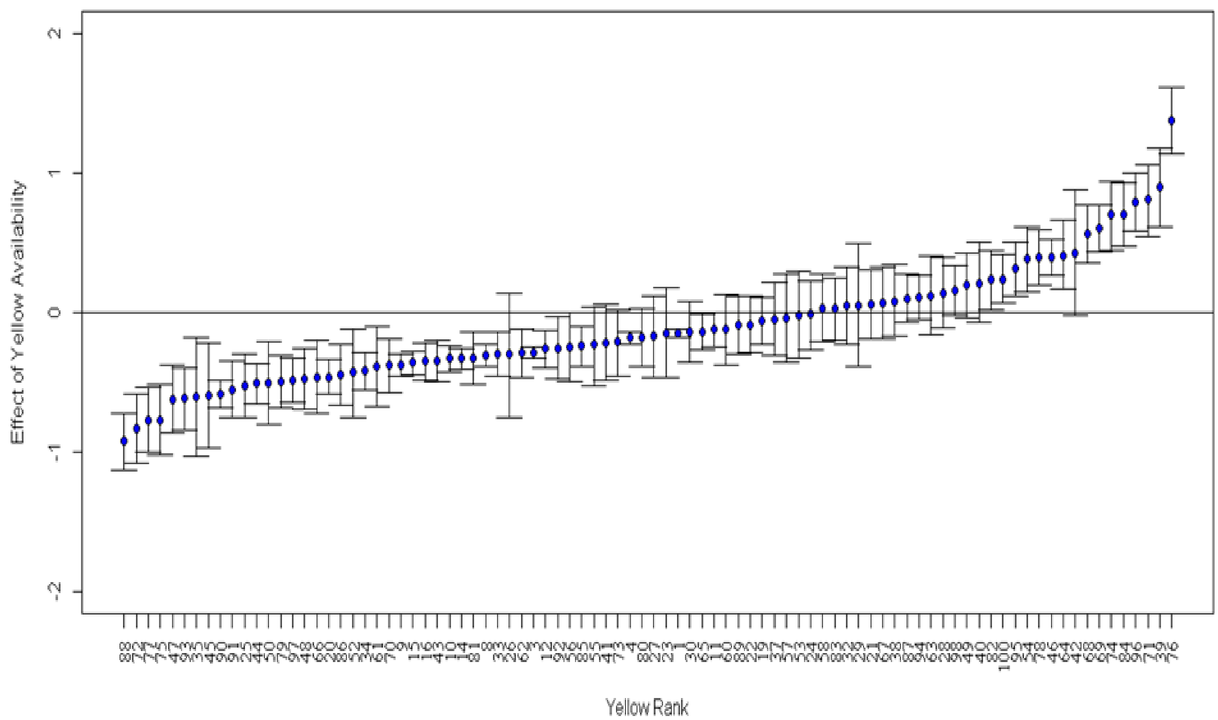
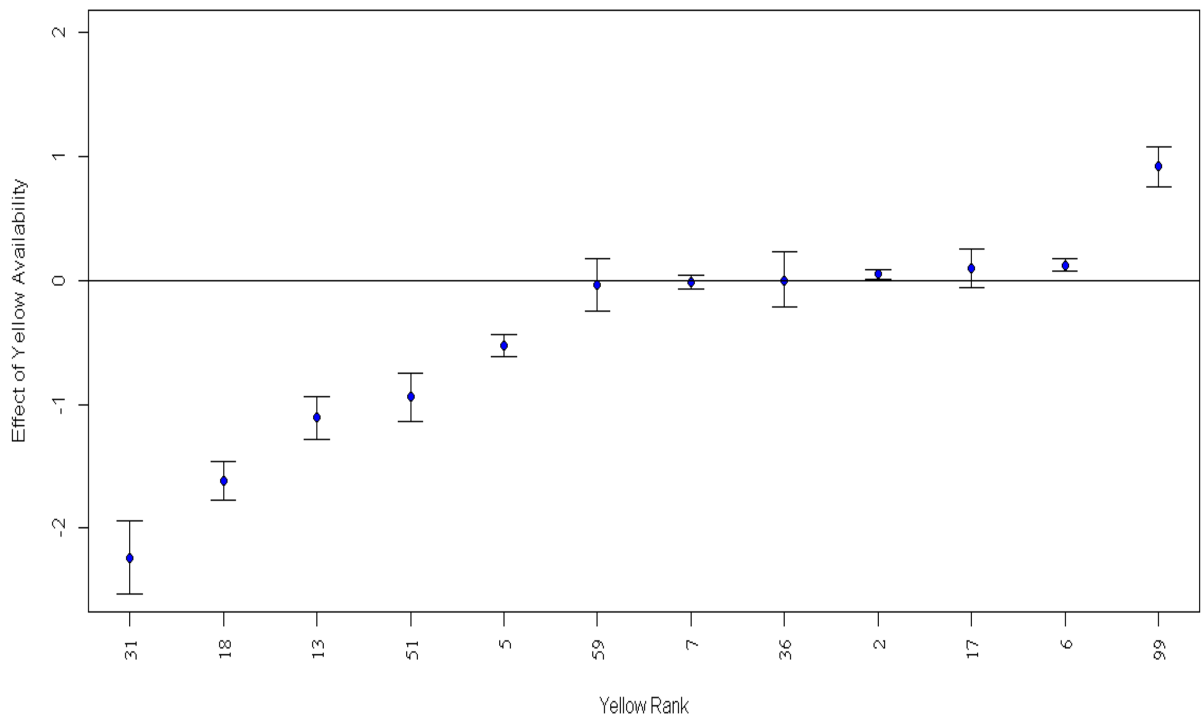


Figure 1.6: Location Specific Model – Segment 2



1.6.3. Robustness Check

Given the potential endogeneity of availability of Yellow Taxi, we take two approaches to assess the reliability of our finding. First, we assume that the availability of Yellow Taxis in each neighborhood could be endogenous with the demand for and availability of paid transportation in the neighborhood. Specifically, we recalibrate our model including two additional covariates as proxies for demand and availability:

$Puclic_{ipt}$ = all the rides taken on public transportation (Subway and Bus) from neighborhood i during period p of day t.

$SubDist_i$ = approximate distance from the center of the neighborhood i to a nearby Subway Station.

Two, we jointly estimate a supply side equation for the availability of Yellow Taxis in the neighborhood at the time of the ride as a function of a 1-week lagged availability of Yellow Taxis in the same neighborhood at the time of the ride and the demand for and availability of public transportation. We include the residual from this equation as an additional covariate in the log-odds model.

Table 1.6: Estimated Parameters of Segment-Specific Model with Outside Goods

Variable	**Mean**	**SD**
Constant	**-0.717**	0.021
Day Time (5 Am to 5 PM)	**0.130**	0.012
Weekend	**-0.309**	0.015
Business/Work	**0.813**	0.023
Leisure	**0.827**	0.024
Residential	**0.851**	0.023
Mean Temperature	0.011	0.007
Mean Rainfall	**0.029**	0.006
Mean Number of Passengers	**0.045**	0.007
Uber Popularity	**0.200**	0.007
Uber Diffusion	**0.445**	0.007
Number of Public Rides	**-0.042**	0.007
Distance to Subway Station	**-0.070**	0.006
Availability of Yellow Taxi in Segment 1	**-0.191**	0.008
Availability of Yellow Taxi in Segment 2	**-0.084**	0.013
Threshold	6.68	
Segment 1	24640	
Segment 2	3360	
Total Number of Observations	28000	

Table 1.7: Estimated Parameters of Segment-Specific Model with Control Function Approach

Variable	Mean	SD
Constant	**-0.749**	0.021
Day Time (5 Am to 5 PM)	**0.135**	0.012
Weekend	**-0.281**	0.014
Business/Work	**0.825**	0.023
Leisure	**0.845**	0.024
Residential	**0.884**	0.023
Mean Temperature	**0.014**	0.007
Mean Rainfall	**0.029**	0.006
Mean Number of Passengers	**0.039**	0.007
Uber Popularity	**0.200**	0.007
Uber Diffusion	**0.455**	0.007
Availability of Yellow Taxi in Segment 1	**-0.208**	0.008
Availability of Yellow Taxi in Segment 2	**-0.079**	0.014
Residual in Segment 1	**0.101**	0.022
Residual in Segment 2	**0.211**	0.038
σ_{ϑ}^{2} – Unobserved Heterogeneity –Main	**0.002**	0.006
Threshold	7.62	
Segment 1	24640	
Segment 2	3360	
Total Number of Observations	28000	
Control Function		
Constant	**0.000**	0.006
Lag-7 Availability of Yellow Taxi	**0.938**	0.006
Number of Public Rides	**0.013**	0.006
Distance to Subway Station	**0.005**	0.006

Bold: 95% credible intervals exclude zero.

The estimated parameters from these models are reported in Table 1.6 and Table 1.7. Findings from both models are very similar to and consistent with those from the proposed model and confirm that there is a threshold distance below (above) which Yellow Taxis (Uber) is the preferred option.

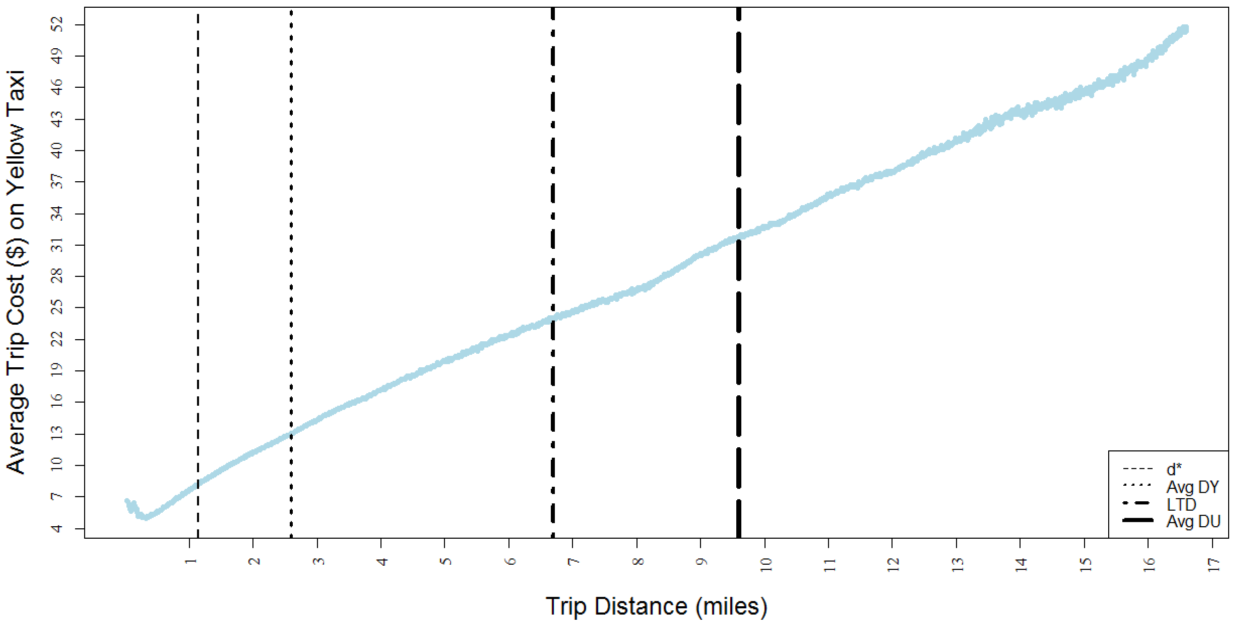
1.7 Discussion

Consumers are increasingly purchasing services through sharing economy platforms as they grow in popularity as suppliers and users. It is critical therefore for SEP's and LP's to understand how consumers choose one of the two options. Sharing economy platforms offer two types of savings to consumers. One, monetary savings, results from lower prices typically offered by sharing economy providers (SEP's) relative to legacy providers (LP's). The second type of savings - hassle savings result from reduced effort and/or time that consumers need to search, identify, and transact with providers. While they may not be able to compete on monetary savings, LP's can still provide hassle savings. In this research, we investigate whether consumers value the two types of savings the relative value they place on each. Specifically, how differences in tariff schedules and secondary service attributes such as availability affect consumer choices. Our empirical results from an investigation of the ridesharing market in New York City suggest that consumers will weigh monetary savings less than hassle savings if the former are below a threshold but that the opposite will be true for larger savings.

1.7.1 Managerial Implication

Our research provides important managerial implications for LP's and SEP's. For additional insights on the role of the threshold distance, as shown in Figure 1.7 we plot the trip distance d* at which the mean monetary cost of a trip on Yellow Taxi and on Uber is approximately the same, the estimated latent threshold, and the mean empirical trip distances on Yellow Taxi rides and on Uber in New York City[4] during the investigation period. Consistent with our findings, the average trip distance on all Yellow Taxis in New York City is below the threshold trip distance and the one for Uber rides is above the threshold (Uber 2014).

Figure 1.7: Average Trip Cost ($) on Yellow Taxi by Trip-Distance (Miles)



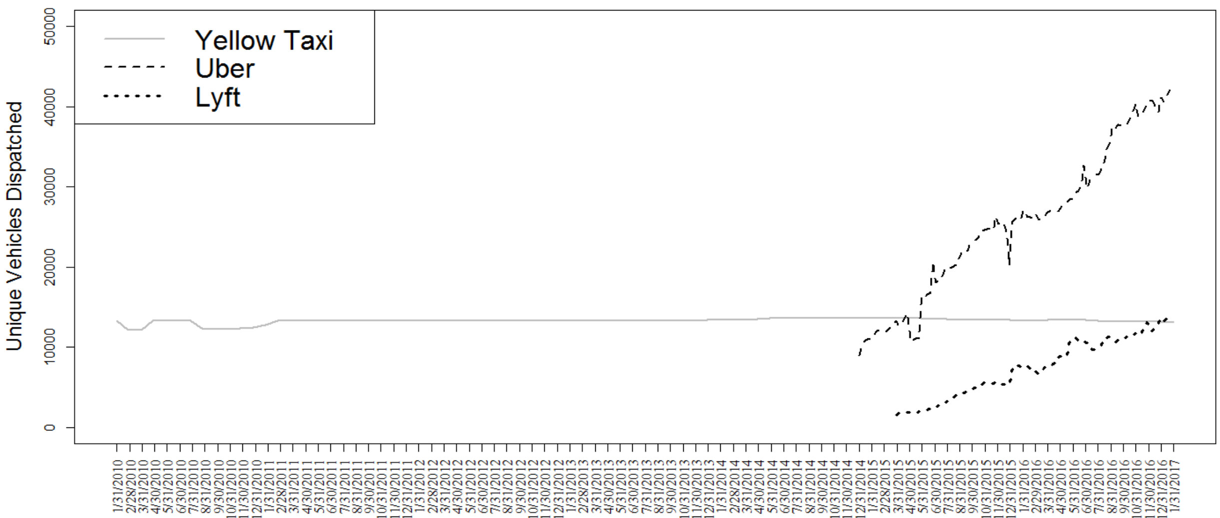
LP's can, therefore, use hassle savings as a strategic variable to retain market share in the short ride-distance segment. As shown in Figure 1.8, while Uber and Lyft have increased the availability, Yellow Taxi has not done so in New York City. The Yellow Taxi should increase availability in order to retain market share in short distance segment, which accounts for around 91% of the total rides in NYC (TLC 2014). At the same time, Uber should consider removing

[4] We compute the average trip distance for all Uber rides in New York City in 2014 based on the average fare for a trip taken on uberX (Uber 2014). For comparison, we compute the average trip distance on all Yellow Taxi rides in New York City in 2014 as well.

minimum fare $8, because around 55% of total rides in NYC city in 2014 are with trip distance less 2 miles.

Figure 1.8: Weekly Dispatch of Unique Vehicles by Service Provider

(January 2010 - January 2017)



Our results also have implications for other service providers where differences between LP’s and SEP’s in pricing structures and secondary attributes may also affect consumer preferences in other shared-economy services. For instance, in the accommodation-sharing market, unlike hotels, AirBNB providers can require a minimum number of days of stay by renters. AirBNB, however, offers more personalized options and flexibility (Zervas et al 2014) than hotels. For example, even when hotels in a location desired by the consumer (e.g., within a few blocks of the shopping district) have no availability for the specific days that she needs, AirBNB may list several available accommodations in that location during those days. On the other hand, AirBNB providers do not offer features like room service and parking and consumers also face more uncertainty than while reserving a room at a branded hotel. The two options would therefore again differ in their transaction costs. Those of the hotel would include the monetary costs of the stay and the opportunity costs of unavailability of the desired dates while those of AirBNB would include the monetary costs, the cognitive costs of uncertainty and the opportunity costs of missing services. Consumers may, therefore, choose between hotels and AirBNB to minimize total transaction costs rather than just the monetary costs.

1.7.2 Limitations and Future Research

Since our empirical analysis is based on data from only one city, we cannot generalize the findings to other cities because demand for paid rides and supply of service may vary by city. However, future studies can consider investigating how the threshold varies, if the data is available for other cities as well. This would help us understand more about how consumers weigh monetary and hassle savings differently depending on the city. Though we provide some insights on how consumers make choices between LPs and SEP's and how differences in tariff schedules and secondary attributes influence consumer choice, there are several avenues for additional research in this area. For instance, the role of uncertainty in consumer choice between LP's and SEP's and how user-generated content like consumer ratings and provider content like photos or videos of the services can reduce uncertainty is one such avenue.

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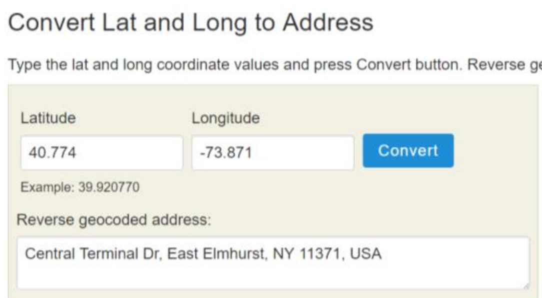
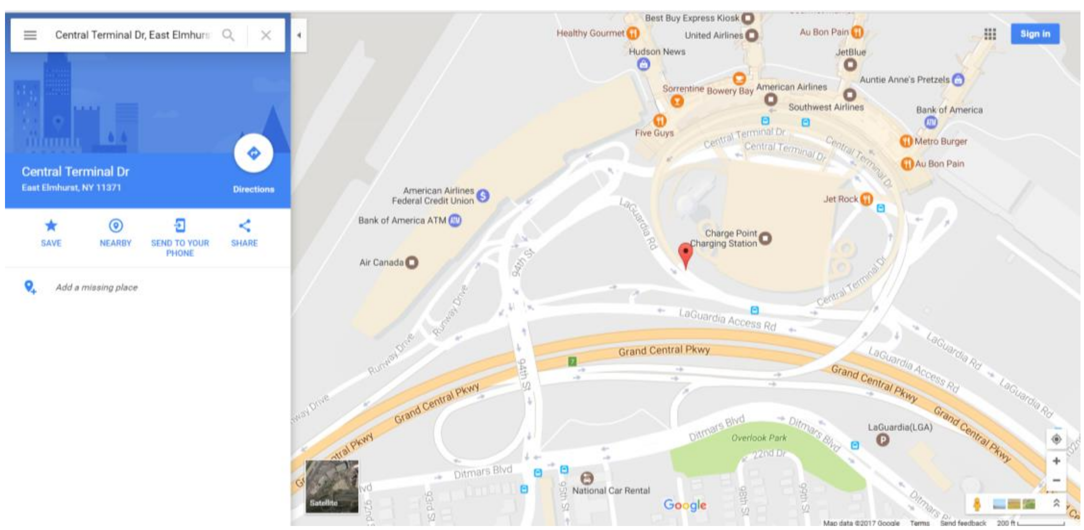
Appendix 1A

First, we convert each longitude and latitude pair (three digits) into an approximate physical address using free software provided at http://www.latlong.net. Then, we rely on data from Google Maps to identify the type of neighborhood in terms of airport, business (corporate headquarters, banks, offices, and other work places), leisure (restaurants, parks, theaters, malls etc.) and residential (houses). An example of Airport type neighborhood:





Essay 2: Variations in the Strategic Value of Hassle Savings

2.1 Introduction

In recent years, the economic importance of a new business model named sharing economy has rapidly grown in the accommodation segment of the tourism and hospitality industry. Airbnb has pioneered this model by hosting a digital platform that allows the large-scale rental of private/shared rooms and entire houses from individuals to other individuals (Bardhi and Eckhardt 2012, Zervas et al 2014). While others such as Wimdu, 9flats, and Roomorama offer a similar type of service, the Airbnb's presence throughout the world has rapidly grown, with more than 3 million listings across 191 countries as of 2016 (CBRE 2017). Airbnb's total valuation stands at $30bn, joining the league of many of the LP's such as the Hilton Group at $20bn and Marriott at $34bn (Forbes 2017).

Accommodations are experience goods because amenities and the quality of services may vary from provider to provider. Whereas providers know the quality of amenities and service prior to the sale, consumers may not, which increases consumers' uncertainty for features and quality of accommodations (Akerlof 1970, Nelson 1970). To reduce uncertainty, consumers, therefore, seek information on the features of accommodations before choosing one. Standardization mostly provides this information in the case of legacy providers like branded hotels. Sharing economy providers, however, cannot rely on standardization since the rented personal accommodations do vary across providers. SEP's, therefore, need to rely on alternative sources of information like user-generated ratings and reviews, reputation systems.

Such reputation systems specifically, are expected to reduce consumers' uncertainty by providing information on the features of accommodations and quality of service through previous consumers' experiences. Prior research indicates that, before making purchase decisions, consumers often seek others' opinions about products and services. Practitioner research (Kee 2008) finds that about 68% of online shoppers read at least four reviews before making a purchase. Similarly, another practitioner study by Forrester finds that most of the consumers look for user ratings and reviews on digital platforms. Above findings suggest that shared accommodation consumers may also be interested in reviews and ratings because such a reputation system provides hassle savings (reduction in uncertainty).

In the first essay, we examined variations in the relative value of monetary and hassle savings with consumption context. In this essay, we investigate whether the value of hassle savings itself varies with consumption context[5]. If it does, the strategic role of the reputation system that provides hassle savings to sharing economy customers will also vary by consumption context for providers. The setting for this essay is AirBNB, which implemented a reputation system where consumers can rate providers after service consumption (Gebbia 2016, Hawlitschek et al. 2016). For empirical analysis, we use the data of 46,738 listings in New York City between April 2016 and October 2017, which is available through InsideAirbnb, a consulting firm. Specifically, our goal is to understand if hosts obtain price premiums for receiving higher ratings from consumers and how those premiums vary across consumption contexts.

In the next section, we review extant literature relevant to our research and develop our research framework. Then, we describe our data, sample selection, and modeling approach. Finally, we present the results, discuss managerial implications and conclude with limitations and direction for future studies.

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[5] We identify 15 consumption contexts based on the combination of five boroughs of New York City and three types of accommodations: (1) *entire* – a house or apartment rented in its entirety (2) *private* – one room in an apartment and (c) *shared* – an accommodation shared by multiple guests.

2.2 Background

In this section, we describe how lack-of-information may affect the Airbnb platform, how Airbnb is alleviating such problem of lack of information by using a reputation system and develop our theoretical framework.

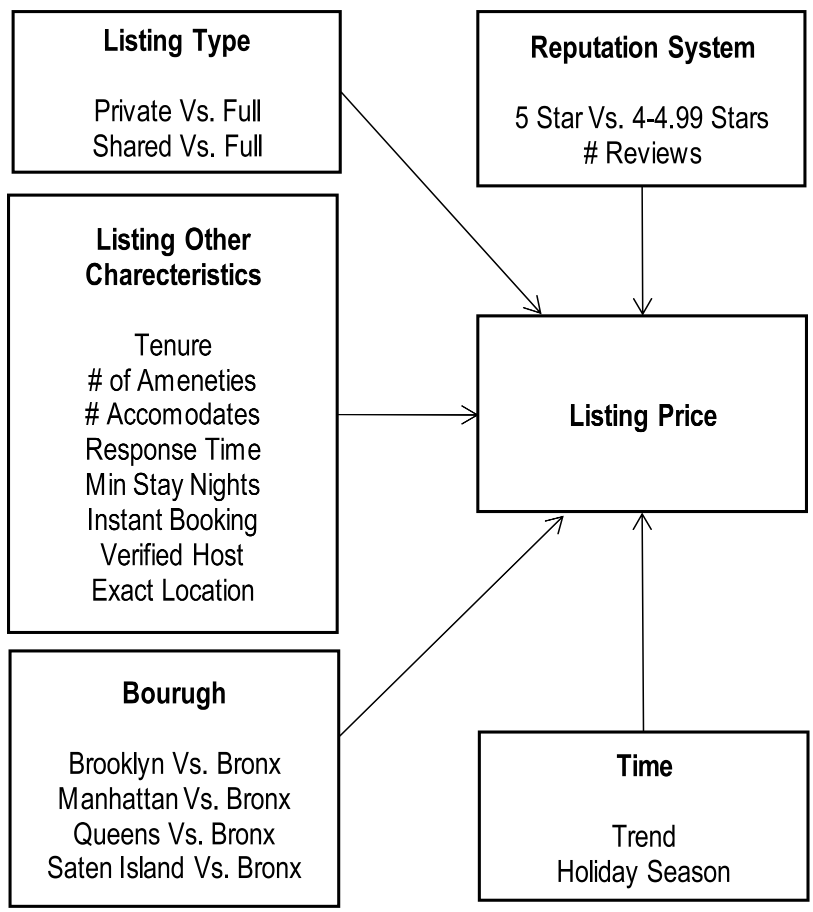
Accommodations are experience goods because amenities and the type and quality of services may vary from provider to provider and consumers face difficulty in observing in advance, but these characteristics can be ascertained upon consumption. Moreover, in contrast to the quality of a room at a branded hotel, it is relatively difficult to make inferences about features of accommodations and service quality on Airbnb, if the provider on Airbnb does not disclose information about features and quality so as to obtain a better rental price (Akerlof 1970). The providers on Airbnb are fully aware of the features of accommodations and its quality while consumers are not, which increases consumers' uncertainty (Nelson 1970, Spence 1973). In general, uncertainty refers to the costs incurred when unexpected outcomes occur as a result of lack-of-information. The aim of a customer is to identify the accommodation that meets her preferences, compares that accommodation with the alternatives having similar features and then to select the most appropriate accommodation with the lowest uncertainty. Consumers, therefore, would like to have access to credible information so that they can reduce uncertainty in making the purchase decision.

Prior literature suggests that consumers can rely on different information pieces as a means of reducing uncertainty (Luhmann, 1979). For example, price (Milgrom and Roberts 1986, Wolinsky 1983), advertising (Ippolito 1990, Kihlstrom and Riordan 1984, Milgrom and Roberts 1986, Nelson 1974, Schmalensee 1978), warranties (Boulding and Kirmani 1993, Grossman 1981, Lutz 1989, Riley 1979, Spence 1977), branding (Dawar and Parker 1994) etc. Similarly, Airbnb, to provide hassle savings to consumers by reducing uncertainty about features of accommodation, has implemented a reputation system where consumers can rate providers after service consumption (Gebbia 2016, Hawlitschek et al. 2016). Consumer ratings are generally found an effective means for reducing uncertainty by establishing trust between peers (Bente et al. 2012, Fuller et al. 2007).

The reputation system is beneficial for the Airbnb since it provides information to the customer about the features and quality of accommodation. This information will give listings with higher rating the ability to differentiate themselves from listings lower rating by charging higher prices as a return for providing hassle savings (reducing uncertainty). Studies that investigated price impact of ratings also suggest that service providers can benefit with such a reputation system. For example, Gutt and Herrmann (2015) find that displaying the rating score for the corresponding Airbnb host for the first time fetched on an average $3 in price premium in New York City. Moreover, the extant literature indicates that different levels of rating scores translate into different prices (Edelman and Luca 2014). These authors analyzed the effect of star ratings in different sub-categories (location, check-in, communication, cleanliness, and accuracy) on Airbnb listing prices, and consistently found higher rating scores to be associated with higher listing prices. Wang and Nicolau (2017) who also find similar results quantified the effect - an additional star is associated with a price markup of 0.87% of listing price. The above findings of price premiums in case of Airbnb are consistent with findings from other settings such as online book or shop reviews (Chevalier and Mayzlin, 2006; Luca 2016).

Above literature suggest that Airbnb consumers realize hassle savings by relying on ratings provided by other consumers to reduce uncertainty about the features and services of listings. In this essay, we investigate whether the value of hassle savings itself varies with consumption context. If it does, the strategic role of features that provide hassle savings to sharing economy customers will also vary for providers. Specifically, our goal is to understand if hosts obtain price premiums for receiving higher ratings from consumers, and our hypothesis is that **higher average rating scores (5.00 vs 4.00-4.99) are associated with higher listing prices.** Further, we hypothesize that depending on the combination of borough and listing type, **these premiums vary across consumption contexts**.

Figure 2.1: Framework



In addition to the main variable of interest, we include many other variables such as service-provider-specific factors and time related (Trend and Holiday Season), which also play a role in pricing decision.

2.3 Methodology

2.3.1 Data and Variables

We use the data provided by InsideAirbnb, an independent consulting firm that collects data from publicly available information from the Airbnb platform. The dataset contains a wide variety of information for all the listings on Airbnb for New York City for monthly observation times from April 2016 to September 2017. In particular, the dataset includes the price of the listing per night, the total number of reviews of the listing, star ratings on a scale from 1 to 5 (converted to 0 to 100 scale), the borough in which the listing is located, the room type etc. For empirical analysis, first, we select 46,738 listings (625,498 monthly observations) which were listed on Airbnb website for at least 6 months during the observation period and have data all the variables of interest that we discuss in the following section. Since the distribution of star ratings is skewed, where practically all ratings are either 5 (19.8%), 4.00-4.99 (55.5%), or 0 (21.5%) stars, for our analysis, we select observations with rating 4.00 or above. This helps us to test the first hypothesis. The descriptive statistics for continuous variables and different indicator variables are displayed in Table 2.1 and 2.2.

$Price_{it}$ is a continuous variable to represent log-transformed price per night of a listing i in the month of t

$Rating5s_{it}$ is an indicator variable to represent whether a listing *i* has a 5 star rating in the month of *t*

$Reviews_{it}$ is a log-transformed continuous variable to represent the number of reviews (volume) a listing *i* has received by the month of *t*

$Tenure_{it}$ is a log-transformed continuous variable to represent the number of days a listing *i* is on Airbnb by the month of *t*

$Private_{it}$ is an indicator variable to represent whether a listing *i* renting a room in an apartment to single guest in the month of *t*

$Shared_{it}$ is an indicator variable to represent whether a listing *i* renting a room in an apartment to multiple guests in the month of *t*

$Brooklyn_{i}$ is an indicator variable to represent whether a listing *i* is located in Brooklyn

$Manhattan_{i}$ is an indicator variable to represent whether a listing *i* is located in Manhattan

$Queens_{i}$ is an indicator variable to represent whether a listing *i* is located in Queens

$SIsland_{i}$ is an indicator variable to represent whether a listing *i* is located in Staten-Island

$Amenities_{it}$ is a log-transformed continuous variable to represent the number of amenities a listing *i* is providing to guests in the month of *t*

$Accomodates_{it}$ is a log-transformed continuous variable to represent the number of people a listing *i* accommodates in the month of *t*

$Response1hr_{it}$ is an indicator variable to represent whether a listing *i* responds to guests within one hour in the month of *t*

$ResponseFhrs_{it}$ is an indicator variable to represent whether a listing *i* responds to guests within few hours in the month of *t*

$MinStay1N_{it}$ is an indicator variable to represent whether a listing i sets minimum stay to one night in the month of t

$MinStay2N_{it}$ is an indicator variable to represent whether a listing i sets minimum stay to two nights in the month of t

$InstantBook_{it}$ is an indicator variable to represent whether a listing i allows instant booking in the month of t

$ExactLoc_i$ is an indicator variable to represent whether a listing i is exactly in the same location as listed on Airbnb

$VerifiedH_i$ is an indicator variable to represent whether a listing i is offered by a verified host

$SuperHost_{it}$ is an indicator variable to represent whether the host of a listing i a super-host in the month of t

$Trend_t$ is a log-transformed continuous variable to represent the number of month in the observation period

$Season_t$ is an indicator variable to represent a month t falls in a holiday-season (November/ December)

Table 2.1: Summary Statistics for Binary Variables for Proposed Sample

Variable	Proportion
Rating 5 Star	0.263
Response Time - 1hr	0.356
Response Time - Few hrs	0.242
Minimum Stay - 1 Night	0.332
Minimum Stay - 2 Nights	0.270
Instant Booking	0.163
Verified Provider	0.736
Exact Location	0.860
Super-Host	0.111
Private	0.455
Shared	0.027
Brooklyn	0.423
Manhattan	0.465
Queens	0.090
Staten-Island	0.006
Season	0.126

Table 2.2: Summary Statistics for Continuous Variables for Proposed Sample

Variable	Mean	SD	MIN	MAX
Price	124.949	70.291	10	399
Volume	22.423	32.895	1	489
Tenure	36.504	20.961	0	113
Amenities	16.227	5.412	2	78
Accommodates	2.763	1.588	1	16
Trend	10.481	5.262	1	19

2.3.2 Model Specification

In this section, we develop our hedonic price function for estimating the effect of a 5-star rating compared to a 4-4.99-star rating on consumers' WTP for listings in New York City.

$$Log(Pirce_{it}) = \beta_0 + \beta_1 Rating5s_{it} + \beta_2 Reviews_{it} + \beta_3 Tenure_{it} + \beta_4 Amenities_{it} + \beta_5 Accomodates_{it} + \beta_6 Response1hr_{it} + \beta_7 ResponseFhrs_{it} + \beta_8 MinStay1N_{it} + \beta_9 MinStay2N_{it} + \beta_{10} InstantBook_{it} + \beta_{11} VerifiedH_i + \beta_{12} ExactLoc_i + \beta_{13} SuperHost_{it} + \beta_{14} Private_{it} + \beta_{15} Shared_{it} + \beta_{16} Brooklyn_i + \beta_{17} Manhattan_i + \beta_{18} Queens_i + \beta_{19} SIsland_i + \beta_{20} Trend_t + \beta_{21} Season_t + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} \sim Normal\ (0, \sigma^2)$$

where β represent the estimated effect of different variables and ε_{it} is random error term.

2.3.3 Model Estimation

We obtain posterior distribution of our parameters in a Bayesian framework using JAGS (Plummer 2003). We use proper but not-informative (Normal with mean zero and large variance) prior for beta coefficients, Gamma distribution with mean one and large variance for the precision parameter. We draw two chains of 25,000 samples with random starting values for the parameters in the Markov chain. We discard the first 15,000 in each chain as burn-in and in the remaining samples; we select every 5th sample and retain total 2,000 from each chain (total 4000 samples) for posterior inference. We monitor the convergence of parameters graphically and using Gelman and Rubin's potential scale reduction factor. We use the value 1.1 or lower for monitoring convergence.

2.4 Results

In this section, we present the findings from the hedonic model with the selected sample. We estimate a hedonic price function to investigate the impact of higher ratings on listing price. We also include many other factors (as discussed in the variables section) into the model to control for the effect these factors have on listing prices. Estimates from the model presented in Table 2.3 are discussed next.

The parameter estimate for a higher rating is significantly positive (**0.051**), which is consistent with the prediction. In other words, listings with a higher average rating (5 stars) can charge a premium of 5.23%[6] compared to listings with a lower rating (4-4.99 stars). Our finding of price premium is consistent with findings from other studies in case of Airbnb (Edelman and Luca 2014, Wang and Nicolau 2017) and other settings such as online book or shop reviews (Chevalier and Mayzlin, 2006, Luca 2016) that listings with higher rating can charge premiums compared to listing with lower ratings.

Estimated effects of other Variables The estimated effects of all the other variables are discussed in this sub-section. While a higher average rating score provides Airbnb listings with strategic value, (i.e. price premiums), a more reliable rating the number of ratings (**-0.003**) has significantly a negative effect on listing price. This surprising finding can be explained using economic theory, assuming the number ratings is a proxy for demand. In other words, the lower listing prices are likely to stimulate demand and hence yield more ratings.

[6] Halvorsen and Palmquist (1980) suggests the binary variable measures the discontinuous effect on the dependent variable, therefore the percentage impact on the dependent variable is: $g * 100 = \{\exp(\beta) - 1\} * 100$

Table 2.3 Parameter Estimates for Hedonic Price Function

Variable	Mean	SD
Constant	**3.894**	0.007
Rating 5 Star	**0.051**	0.001
Volume	**-0.003**	0.001
Tenure	**0.058**	0.001
Amenities	**0.105**	0.002
Accommodates	**0.279**	0.001
Response Time - 1hr	**-0.005**	0.001
Response Time - Few hrs	0.001	0.001
Minimum Stay - 1 Night	**0.012**	0.001
Minimum Stay - 2 Nights	**0.040**	0.001
Instant Booking	**-0.035**	0.001
Verified Provider	**-0.013**	0.001
Exact Location	0.000	0.001
Super-Host	**0.073**	0.002
Private	**-0.541**	0.001
Shared	**-0.867**	0.003
Brooklyn	**0.248**	0.004
Manhattan	**0.531**	0.004
Queens	**0.142**	0.005
Staten-Island	0.009	0.008
Trend	**-0.025**	0.001
Season	**0.007**	0.002

Bold: 95% credible intervals exclude zero.

Similarly, Instant booking (**-0.035**) and trend (**-0.025**) have significantly negative effects on listing price. While this is a positive amenity that helps the consumers plan their trip in an easier way, it is linked to lower prices. It seems Airbnb providers combine both strategies 1) lower prices over the period to be more attractive and 2) instant booking to be easier to be reserved to increase the demand.

Airbnb displays explicitly the time at which a provider registered on the platform and assigns qualified hosts with a super-host badge. Consistent with intuition, the tenure (**0.058**) and super-host (**0.073**) variables have significantly positive effects on listing price. As Airbnb actively seeks to create a community of long-term engagement (Gebbia, 2016), tenure and super-hosts act as a proxy for the reputation of the host. The examination of the other attributes reveals intuitively consistent results. For instance, the listings that rent either private rooms (**-0.541**) or shared rooms (**-0.867**) are able to charge a lower price than listings that rent entire homes/apartments (which is our reference category in the hedonic regression). The parameter estimates for markets (boroughs) indicate significant geographic differences in listing prices. For example, compared to Bronx, the listings in Brooklyn (**0.248**), Manhattan (**0.531),** Queens (**0.142**), and Staten-Island (0.009) can charge more price. This result could be due to the variation in real estate or rental prices in corresponding markets. The number of people accommodated (**0.279),** the number of amenities (**0.015**), minimum stay (one night: **0.012**, two nights: **0.040**), and season (**0.007**) all have positive and significant parameters.

2.4.2. Consumption Context Models

Our findings from the pooled model in the previous section suggest that Airbnb consumers realize hassle savings by relying on ratings provided by other consumers to reduce uncertainty about the features and services of listings. The value of the savings, however, would vary with the level of uncertainty. Specifically, we hypothesized that uncertainty is likely to be higher under two consumptions contexts. One, where the number of listings in a location is very large. Two, where the number of listings and hence the number of ratings is small. We investigate if these are indeed the patterns by estimating hedonic models of rental prices for listings in the five boroughs of New York City for three types of accommodations: (1) entire – a house or apartment rented in its entirety (2) private – one room in an apartment and (c) shared – an accommodation shared by multiple consumers.

In each of the borough-type combinations, we assume that listings that receive an average rating of 5.0 are the treatment group and those with ratings of 4.0 – 4.99 are part of the control group. We then use propensity score matching to identify the treatment and control samples for each of the combinations. Table 2.4 shows the number of observations in each treatment and control group by sub-sets. We, however, did not have sufficient data for one of the fifteen combinations (Shared room type in Staten-Island) and therefore investigate each of the other fourteen borough-type combinations. Results from these fourteen models are showed in Table 2.5 (Entire type by Market), in Table 2.6 (Private type by Market) and in Table 2.7 (Shared type by Market). Estimates of the effect of a higher rating on the price premium are consistent with our hypotheses. As shown in Table 2.9 and Figure 2.2, premiums are higher in combinations that have fewer listings or have a large number of listings.

Table 2.4: Sample Size for Consumption Context Models

Market	Room Type	Treatment	Control	Total	Number of Observations for Causality Model
Bronx	Entire	516	1577	2093	1032
	Private	1148	3567	4715	2296
	Shared	99	243	342	198
Brooklyn	Entire	26684	71443	98127	53368
	Private	27590	69145	96735	55180
	Shared	1251	3118	4369	2502
Manhattan	Entire	32136	93814	125950	64272
	Private	21707	65166	86873	43414
	Shared	1496	4788	6284	2992
Queens	Entire	4237	12058	16295	8474
	Private	5873	18526	24399	11746
	Shared	440	1320	1760	880
Staten-Island	Entire	287	905	1192	574
	Private	463	1285	1748	926
	Shared	0	18	18	0
Total		123927	346973	470900	247854

Table 2.5: Parameter Estimates for Entire Segment by Market

Variable	Bronx		Brooklyn		Manhattan		Queens		Staten-Island	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Constant	**4.114**	0.117	**3.902**	0.015	**4.382**	0.014	**4.029**	0.032	**4.370**	0.163
Rating 5 Star	0.045	0.026	**0.072**	0.004	**0.057**	0.004	**0.047**	0.009	0.053	0.028
Volume	**-0.053**	0.012	**0.004**	0.002	**0.010**	0.002	-0.005	0.004	**-0.058**	0.013
Tenure	**0.080**	0.013	**0.072**	0.002	**0.033**	0.002	**0.059**	0.005	0.026	0.017
Amenities	0.066	0.041	**0.162**	0.005	**0.148**	0.004	**0.097**	0.010	**-0.128**	0.045
Accommodates	**0.261**	0.021	**0.318**	0.004	**0.241**	0.004	**0.316**	0.008	**0.684**	0.024
Response Time - 1hr	**-0.069**	0.027	**-0.014**	0.004	**0.023**	0.004	**-0.032**	0.009	**-0.173**	0.033
Response Time - Few hrs	-0.005	0.027	0.000	0.004	**0.016**	0.004	0.001	0.009	**-0.168**	**0.039**
Minimum Stay - 1 Night	**-0.091**	0.026	**-0.014**	0.004	**-0.016**	0.003	**0.023**	0.009	-0.036	**0.031**
Minimum Stay - 2 Nights	0.021	0.024	**0.040**	0.004	**0.044**	0.003	**0.077**	0.009	0.022	0.032
Instant Booking	-0.005	0.026	**-0.053**	0.006	**-0.043**	0.005	**-0.027**	0.012	0.022	**0.030**
Verified Host	0.008	0.022	**-0.018**	0.004	0.000	0.003	**-0.064**	0.008	**-0.133**	**0.032**
Exact Location	**-0.052**	0.022	**0.009**	0.005	**-0.010**	0.004	0.004	0.010	**0.090**	**0.032**
Super-Host	0.007	0.043	**0.065**	0.007	**0.029**	0.008	**0.047**	0.014	-0.003	**0.036**
Trend	**-0.030**	0.015	**-0.029**	0.002	**-0.022**	0.002	**-0.030**	0.005	-0.021	0.017
Season	0.017	0.031	**0.000**	0.005	**0.010**	0.004	0.006	0.011	-0.033	**0.036**

Bold: 95% credible intervals exclude zero.

Table 2.6: Parameter Estimates for Private Segment by Market

Variable	Bronx		Brooklyn		Manhattan		Queens		Staten-Island	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Constant	**3.683**	0.054	**3.548**	0.013	**3.906**	0.016	**3.645**	0.024	**3.612**	0.105
Rating 5 Star	**0.098**	0.015	**0.051**	0.004	**0.076**	0.005	**0.031**	0.007	**0.211**	0.027
Volume	**-0.019**	0.007	**0.006**	0.002	**0.017**	0.002	**-0.019**	0.003	**-0.040**	0.011
Tenure	**0.067**	0.008	**0.082**	0.002	**0.052**	0.003	**0.067**	0.004	**0.066**	0.013
Amenities	**0.045**	0.017	**0.087**	0.004	**0.082**	0.005	**0.074**	0.008	-0.035	0.033
Accommodates	**0.242**	0.016	**0.262**	0.004	**0.244**	0.005	**0.272**	0.008	**0.317**	0.029
Response Time - 1hr	**-0.091**	0.016	0.003	0.004	**0.015**	0.005	**-0.071**	0.008	**-0.167**	0.028
Response Time - Few hrs	**-0.112**	0.017	**-0.010**	0.004	**0.023**	0.005	**-0.020**	0.008	**-0.093**	0.031
Minimum Stay - 1 Night	**0.115**	0.015	**0.057**	0.003	**0.068**	0.004	**0.066**	0.007	**0.318**	0.030
Minimum Stay - 2 Nights	**0.043**	0.016	**0.068**	0.004	**0.057**	0.005	**0.126**	0.009	**0.266**	0.037
Instant Booking	**-0.040**	0.016	**-0.027**	0.005	**-0.049**	0.006	**0.022**	0.008	0.013	0.027
Verified Host	**-0.083**	0.015	**-0.023**	0.003	**0.014**	0.004	**-0.046**	0.006	**-0.226**	0.023
Exact Location	**-0.050**	0.016	-0.007	0.004	**-0.018**	0.005	**-0.039**	0.007	**0.058**	0.029
Super-Host	**0.075**	0.019	**0.089**	0.007	**0.046**	0.008	**0.066**	0.010	**0.077**	0.031
Trend	**-0.025**	0.010	**-0.031**	0.002	**-0.024**	0.003	**-0.020**	0.004	0.007	0.015
Season	0.002	0.018	0.007	0.004	**0.011**	0.006	0.008	0.009	0.038	0.033

Bold: 95% credible intervals exclude zero.

Table 2.7: Parameter Estimates for Shared Segment by Market

Variable	Bronx		Brooklyn		Manhattan		Queens	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Constant	**3.721**	0.229	**3.070**	0.069	**3.285**	0.080	**3.573**	0.111
Rating 5 Star	0.082	0.050	**0.191**	0.023	**0.138**	0.024	**0.124**	0.038
Volume	**-0.109**	0.029	-0.003	0.010	0.018	0.010	-0.016	0.017
Tenure	-0.064	0.048	**0.124**	0.011	**0.167**	0.012	-0.001	0.019
Amenities	**0.173**	0.048	0.020	0.020	**0.106**	0.023	0.034	0.035
Accommodates	-0.077	0.062	**0.112**	0.016	**0.238**	0.019	**0.075**	0.026
Response Time - 1hr	-0.054	0.058	**-0.151**	0.023	**-0.129**	0.022	**-0.150**	0.039
Response Time - Few hrs	-0.044	0.072	**-0.168**	0.023	**-0.137**	0.022	-0.074	0.042
Minimum Stay - 1 Night	0.027	0.126	**0.253**	0.022	-0.023	0.023	**0.171**	0.036
Minimum Stay - 2 Nights	-0.029	0.144	**0.260**	0.028	-0.031	0.029	**0.268**	0.067
Instant Booking	-0.063	0.062	**-0.107**	0.026	0.004	0.031	**-0.085**	0.036
Verified Host	-0.106	0.074	0.015	0.022	0.009	0.021	**0.086**	0.034
Exact Location	**-0.291**	0.056	-0.025	0.023	-0.039	0.024	-0.032	0.035
Super-Host	0.190	0.138	-0.001	0.028	0.006	0.043	**-0.195**	0.047
Trend	**0.076**	0.032	**0.031**	0.013	0.014	0.012	-0.006	0.024
Season	0.010	0.080	-0.009	0.026	-0.008	0.027	0.093	0.045

Bold: 95% credible intervals exclude zero.

Table 2.8: Average Distribution Intensity (%) of Listings in New York City (Proposed Sample)

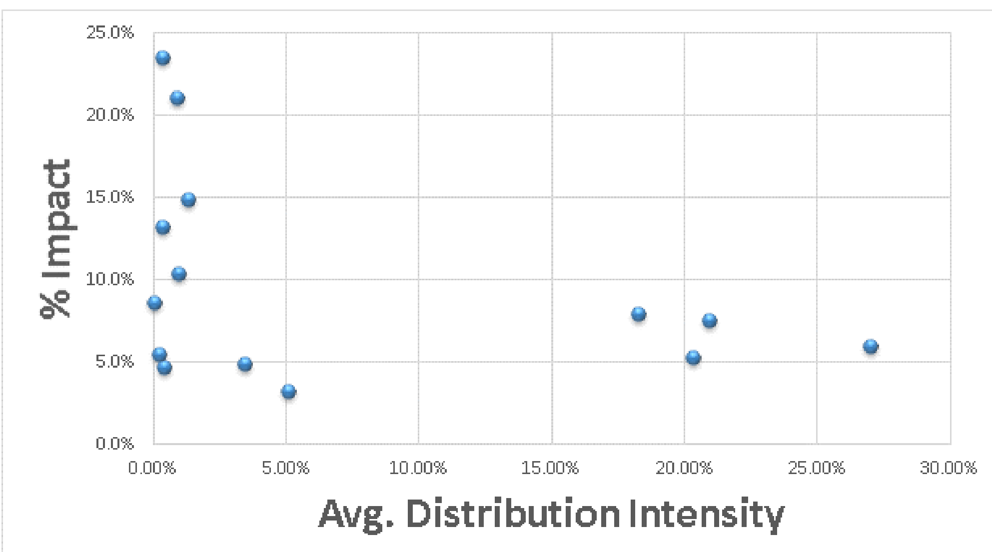
Room Type / Market	Bronx	Brooklyn	Manhattan	Queens	Staten-Island	Total
Entire	0.44%	20.94%	27.02%	3.50%	0.25%	52.14%
Private	0.99%	20.34%	18.29%	5.15%	0.38%	45.15%
Shared	0.08%	0.93%	1.33%	0.36%	0.00%	2.71%
Total	1.50%	42.21%	46.65%	9.01%	0.63%	100.00%

Table 2.9: Percentage Impact of Higher Rating on Listing Price

Room Type / Market	Bronx	Brooklyn	Manhattan	Queens	Staten-Island
Entire	**4.50%**	**7.20%**	**5.70%**	**4.70%**	**5.30%**
Private	**9.80%**	**5.10%**	**7.60%**	**3.10%**	**21.10%**
Shared	**8.20%**	**19.10%**	**13.80%**	**12.40%**	NA

Bold: 95% credible intervals exclude zero.

Figure 2.2: Percentage Impact of Higher Rating on Listing Price



2.5 Discussion

Consumers are increasingly purchasing accommodation services through sharing economy platforms such as Airbnb as they grow in popularity. Accommodations are experience goods because amenities and the type and quality of services may vary from provider to provider. Whereas providers know the quality of service prior to the sale, consumers may not, increasing uncertainty (Akerlof 1970, Nelson 1970). It is critical therefore for SEP's to understand how consumers reduce uncertainty about accommodation services and make their purchases. Prior literature suggests that consumers seek information on the features of accommodations before choosing one to reduce uncertainty. Airbnb has implemented a reputation system where consumers can rate providers after service consumption (Gebbia 2016, Hawlitschek et al. 2016). Such reputation systems provide consumers with hassle savings (reduced uncertainty), and hence providers with strategic value. The value of the savings should, therefore, be higher in consumption contexts with greater uncertainty. In this research, we investigate whether the value of hassle savings itself varies with consumption context. We hypothesize that uncertainty is likely to be higher under two consumptions contexts. One, where the number of listings in a location is very large. Two, where the number of listings and hence the number of ratings is small. Estimates of the effect of a higher rating on the price premium are consistent with our hypotheses. Premiums are higher in combinations that have fewer listings or have a large number of listings.

2.5.1 Managerial Implications

Our findings provide insights into how sharing economy providers can capitalize on the reputation system. As the strategic role of features that provide hassle savings to sharing economy customers vary for providers by consumption contexts, providers should then invest more in features that provide hassle savings in contexts where they are valued more but can reduce such investments in other contexts.

2.5.2 Limitations and Future Research

Though we provide insights into how Airbnb or other service providers can benefit by providing information through reputation system to consumers to reduce uncertainty, we acknowledge two main limitations of this study. First, we focused mainly on the price impact of reputation systems, though we include various other factors. However, no social or psychological factors influencing hosts' price decisions are considered. Therefore, future studies can conduct more research to explore the rationale for the hosts' price increase or decrease decisions. Second, due to data limitations, the scope of this study is limited to rentals in the city of New York City. Future studies can analyze panel data for a few more cities to generalize the results.

Though we provide some insights on how consumer prospects reduce uncertainty and make their purchase on Airbnb, there are several avenues for additional research in this area. For instance, the role of uncertainty in consumer choice between LP's such as Hotels and SEP's such as Airbnb. How providers' content like photos or videos of the services can reduce uncertainty is another such avenue.

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Essay 3: Social Relationships as Strategic Variable in the Accommodation-Sharing Market

3.1 Introduction

The market for accommodation services traditionally involves consumers and prospects renting accommodations from legacy providers (LP's), such as hotels. Sharing economy service providers (SEP's) like Airbnb has shaken up this model by hosting digital platforms that allow the large-scale rental of private/shared rooms and entire houses from individuals to other individuals (Bardhi and Eckhardt 2012, Zervas et al 2014). While others such as Wimdu, 9flats, and Roomorama offer a similar type of service, the Airbnb's presence throughout the world has rapidly grown, with more than 3 million listings across 191 countries as of 2016 (CBRE 2017). Airbnb's total valuation stands at $30bn, joining the league of many of the LP's such as the Hilton Group at $20bn and Marriott at $34bn (Forbes 2017).

Due to Airbnb's affordable and authentic experiences with a range of accommodations, the number of consumers staying at Airbnb hosts has been rapidly growing. Since Airbnb's founding in 2008, approximately 140 million consumers stayed at Airbnb hosts worldwide, including nearly 80 million in 2016, up from 40 million in 2015 (Airbnb 2017). In terms of revenue for the period October 2015 to September 2016, over 416,000 Airbnb hosts in the United States generated an estimated $5.7 billion, which was a 140% increase over the preceding 12-month period (CBRE 2017).

In contrast to rides (as in Essay 1) that are search goods – ride distance does not vary across providers - accommodations are experience goods because amenities and the type and quality of services may vary from provider to provider. Consumers, therefore, seek information on the features of accommodations before choosing one. Standardization mostly provides this information in the case of legacy providers like branded hotels. Sharing economy providers, however, cannot rely on standardization since the rented personal accommodations do vary across providers. Consumers, therefore, need to rely on alternative sources of information like user-generated ratings and reviews (as in Essay 2). We found that Airbnb reputation system provides consumers with hassle savings (reduced uncertainty), and providers with strategic value (price premiums).

An additional source that sharing economy providers have been offering is information on whether the host or any previous renters of a shared accommodation are acquaintances of a prospective renter. Airbnb, for instance, offers this through a feature called *social connections* that allows visitors to see only those accommodations reviewed by their friends or friends of friends on Facebook. The feature thus provides *hassle savings* by reducing search costs and can, therefore, be a strategic variable in the accommodation market. We investigate its effect in this research.

Our empirical analysis involves data on the search and time to the first purchase of a sharing accommodation by those who register on the Airbnb site. We examine two outcomes: (1) whether or not a purchase occurs (2) time to purchase if one occurs. The data includes 35,741 consumers who registered between January 2014 and June 2014. For our empirical analysis, we select 4,316 consumer prospects who have used social connection feature at least once. We use a proportional hazards model to relate time to first purchase to our primary variable of interest – social connections. We operationalize social connections as the number of times that a registered user uses the social connections feature before making the first purchase or terminating the search without a purchase. We also control for the effects of demographics (gender and age), how a registered user first arrived at the Airbnb site (e.g., via a link on Facebook or a search engine), and the number devices she uses for accessing the Airbnb site. We model the occurrence of the purchase/non-purchase of an accommodation as a binary logit related to the same variables and model the two outcomes jointly in a Bayesian framework. Our findings indicate a significant effect of social connections in reducing the time to, and increasing the likelihood of, the first purchase.

The social connections variable could, however, be endogenous with search time. Those who have friends on Facebook may be more experienced online users and hence, faster in searching and more willing to purchase, online. Additionally, they may be using the social connections feature only because it allows them to see which of their friends may be hosts or had used accommodations they are also considering. We take two approaches to investigate whether there are alternative explanations for our findings. First, we use propensity score matching (PSM) with 4,316 consumer prospects who have used social connection feature at least once as the treatment group matched with those who do not use this feature and re-estimate my models on the pooled sample. We use the signup method, which indicates whether people used Facebook/Google to set up an account on Airbnb before searching for accommodations. We also use age as a matching variable as a proxy for experience with- and interest in- using social media and learning about friends' activities. Results from this re-estimation are consistent with our findings and indicate that social connections are indeed reducing search time and increasing the likelihood of a purchase.

Second, we exploit possible geographic differences in the hassle savings' value of social connections to validate our findings. Specifically, we hypothesize that the value of hassle savings should be larger when someone is searching internationally rather than domestically in the US since uncertainty should be higher with the former. We, therefore, re-estimate our model with geographic-specific estimates of the effects of social connections. We do find that the effects are larger both on the time to make the first purchase and on the likelihood of the first purchase for international listings than domestic ones. Our research has several managerial implications. It provides insights into how sharing economy platforms can shorten the time taken by prospective customers to make their first purchases through the platforms.

In the next section, we discuss extant literature relevant to present research and develop our theoretical framework. In section 3, we discuss our data and modeling approach. Finally, we discuss the results and managerial implications and conclude with limitations and direction for future studies.

3.2 Background

3.2.1 Reasons for Delay

Several research studies have investigated why people delay their decisions or tasks in different contexts: daily tasks (Milgram et. al.1988), personal projects (Lay 1986), and term-paper writing by students (Solomon and Rothblum 1984). In consumers' purchase decisions context, Greenleaf and Lehman (1995) developed comprehensive typologies of reasons why consumers delay purchase decisions and suggest that the delay time considerably exceeds the active decision time (time used for gathering additional information, evaluating different alternatives, and making the actual purchase decision) and studying total delay time would explain why one purchase quickly while the others delay for months. Authors developed six propositions: (1) perceived lack of time to devote to the decision, (2) shopping for the product is unpleasant, (3) perceived risk, (4) seeking advice from others, (5) procedural uncertainty, and (6) gathering more information on alternatives. Though there are many reasons behind consumer decision to delay the purchase in the general shopping context, one of the most critical reasons for the delay is reducing "perceived risk" or "uncertainty" (Corbin 1980, Darpy 2000, Greenleaf and Lehman 1995).

3.2.2 Perceived Risk

Since the introduction by Raymond A. Bauer in 1960, the concept of "perceived risk" or "uncertainty" has been widely studied over the past six decades in the marketing literature (Bauer 1960). According to Bauer (1960, p. 390), "Consumer behaviour involves risk in the sense that any action of a consumer will produce consequences which he cannot anticipate with anything approximating certainty, and some of which at least are likely to be unpleasant". Cox (1967) suggests that a decision situation is risky when a consumer is uncertain about the consequences of her choice. Cunningham (1967, p. 37) conceptualized perceived risk in terms of two similar components, namely; the amount that would be lost (i.e. that which is at stake) if the consequences of an act were not favorable, and the individual's subjective feeling of certainty that the consequences will be unfavorable.

Though perceived risk has been defined in many ways in literature, in sum, all the definitions of perceived risk suggest that consumers face a certain level of risk or uncertainty while making purchases. Previous studies in the marketing literature have used six different risk dimensions to explain consumers' purchase decisions: performance, financial, physical risk, social, psychological, and time or convenience risk (Stone and Gronhaug 1993). Jacoby and Kaplan (1972) distinguished between five risk dimensions such as (1) financial risk (how the purchase may affect value-for-money i.e. the possibility that the product will not be worth the cost of purchase), (2) performance risk (how the purchase may perform i.e. the possibility that the product or service chose might not perform as desired and thus not deliver the benefits promised), (3) physical risk (how the purchase may affect our physical well-being), (4) social risk (how the purchase might affect what others think of us i.e. the possibility that a purchase will not match the opinions of reference groups), and (5) psychological risk (how purchase might affect what we think of ourselves i.e. the possibility that a purchase cannot satisfy the consumer's self-image). Roselius (1971) suggested that time-related risk is also another important dimension for studying consumer purchase decisions: (6) time-loss risk (opportunity cost of time i.e. the possibility that the time for planning, purchasing execution will not be worth).

Though perceived risk is multi-dimensional, as previously discussed, extant marketing literature has widely investigated the role of financial and performance risk dimensions in addition to overall risk in consumer choice (Agarwal and Teas 2001, Conchar et al. 2004, Grewal et al. 1998, Shimp and Bearden 1982, Sweeney et al. 1999). However, social risk (Campbell and Goodstein 2001, Stone and Gronhaug 1993) and psychological risk (Dowling and Staelin 1994) appear particularly interesting for products that are visible to others and communicate the consumer's self-image such as apparels and electronic gadgets. In cases of services, in addition to financial and performance risk, due to the inseparability of service production and consumption, consumers' personal involvement with services causes the social and psychological loss to be more salient as well (Mitchell and Greatorex 1993, Murray and Schlacter 1990). Time-loss also feature greatly as this type of risk is linked to the total cost of the product or service.

3.2.2.1 Risk Reduction Strategies

Bauer (1960) suggests that consumers develop or adopt different strategies to reduce perceived risk, which allows consumers to make purchase decision more confidently (for review: Mitchell and McGoldrick 1996). Roselius (1971) identifies 11 such strategies: endorsements, brand loyalty, brand image, private testing, store image, free samples, money-back guarantees, government testing, shopping, expensive models, and word-of-mouth communications.

Information seeking is the most convenient and efficient method for consumers to reduce perceived risk. Several studies have examined the relationship between perceived risk and information search activity and suggest that consumers employ information search as a problem-solving strategy to reduce perceived risk (Dowling and Staelin 1994 Smith and Bristor 1994, Srinivasan and Ratchford 1991). The underlying motivation in the relationship between perceived risk and information search is that when consumers make purchases associated with greater purchase risk or uncertainty such as expensive products and different services etc., consumers increasingly engage in an extensive search for- or seek more- information. Furthermore, since services are high in credence qualities, consumers tend to perceive service as risky purchases. Such a characteristic of services increasingly promotes pre-purchase information search (Murray, 1991, Murray and Schlacter 1990).

Perceived risk determines not only the level of information search activity but also the sources of information (Cox 1967, Locander and Hermann 1979), as different sources meet different information needs such as advertisements in general media or in specific media e.g, brochures, and word-of-mouth etc. Cox (1967) categorized information sources into three sources: (1) marketer dominated, (2) consumer dominated, and (3) neutral. While marketer-dominated sources (i.e. packaging, promotion, advertising) were controlled by the marketer, consumer-dominated sources referred to interpersonal informational channels over which the marketer has little control. For example, independent review and ratings by other consumers which provides first-hand information about the product or brand (Bansal and Voyer 2000, Mitchell and Vassos 1997). Neutral sources (i.e. consumer reports, newspapers) were controlled neither by the marketer nor by the consumer. If a consumer perceives a particular source of information more reliable and valuable, consumers expect to heavily use that information source to reduce her perceived risk.

For example, Arndt (1967, pg. 294) studied the relations between perceived risk in trying a new brand of coffee and word-of-mouth and found that "the high-risk perceivers tended to make more effort to seek word-of-mouth information".

Purchasing known brands is another leading strategy that consumers use to reduce perceived risk. Brands act as important heuristic that consumers use to reduce perceived risk while making purchases (Bauer 1960, Bauer and Cox 1967, Berthon et al. 1999, Park and Lessig 1981, Sheth and Venkatesan 1968, Zeithaml 1981), as brand names in general signal for product quality (Rao et al. 1999). As consumers repeatedly purchase the same the brand, they develop brand loyalty, which is the most effective in reducing consumer perceived risk (Bauer 1960, Mitchell and Greatorex 1993).

Extant literature suggests that consumers reduce perceived risk by obtaining someone else's advice or assistance such as friends, family members, purchase-pals, and salespeople (Amato and Bradshaw 1985, Greenleaf and Lehman 1995). Murray (1991) found that service consumers also prefer to seek information from family, friends, and peers rather than sponsored promotional sources. Mitchell and McGoldrick (1996) suggest that consumer may seek information/opinions from family members or friends on a product and use that information alone or together with other information of the product in making purchase decisions. Greenleaf and Lehman (1995) suggest that "Consumers delay decision making because they rely on advice from others and cannot easily or immediately obtain this advice."

3.3 Framework

The extant literature, however, shows little exploration into the concept of consumer-focused risk reduction strategies such as social connections, particularly within a domain-specific context such as accommodation services in sharing economy.

A few studies focused on social networks suggests that social networks allow individuals to easily share product experiences and information with others (Chen et al. 2011). On these social networks, consumers can have social interaction and become familiar with one another, providing a possible source of trust (Lu et al. 2010) and social support (Ridings & Gefen 2004). These interactions can greatly influence consumers' willingness to purchase (Gefen 2002).

3.3.1 Social Connections

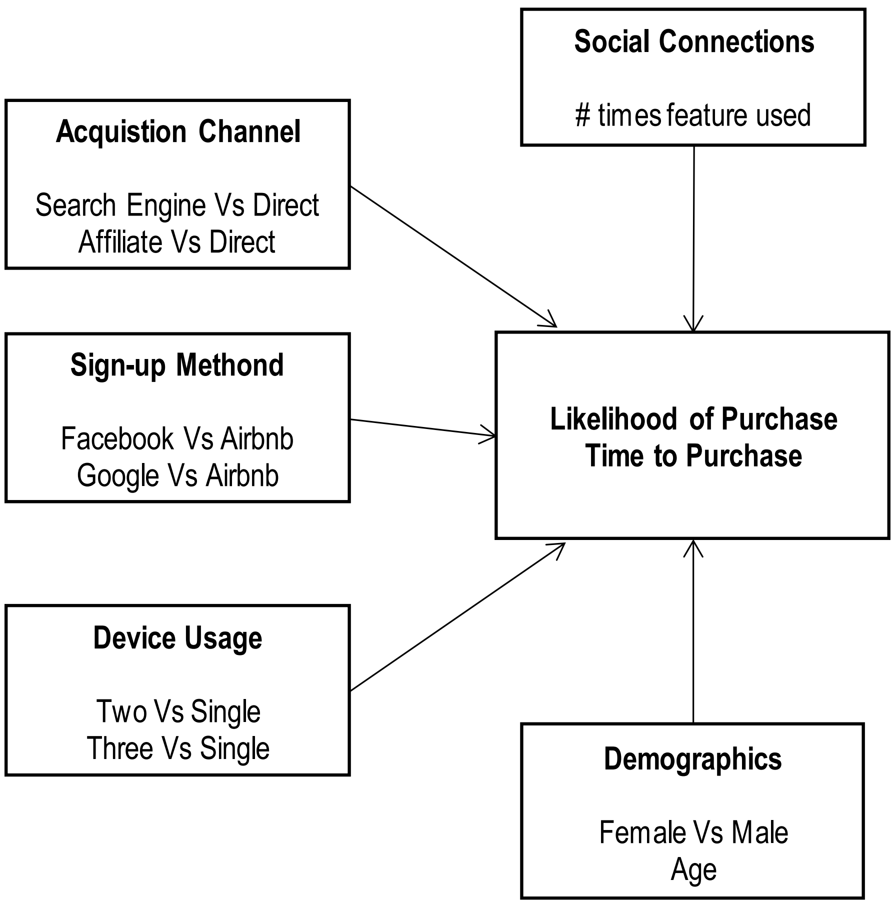
In 2011, Airbnb created *social connection* feature to provide hassle savings by reducing consumers' perceived risk or uncertainty. This additional source that Airbnb has been offering is information on whether the host or any previous buyers of a shared accommodation are acquaintances of a prospective renter. It also allows consumers to share Airbnb activity such as recent locations visited their Facebook friends who are also on Airbnb (Airbnb 2011). When consumer prospects search for listings around the world, they see an avatar if a Facebook friend is a friend of the host or has reviewed the host.

In the context of consumer prospects booking accommodations at Airbnb, based on the literature previously discussed, we argue that consumers can use the social connection feature as a risk reduction strategy. Social connection feature thus provides hassle savings by reducing search costs and can, therefore, be a strategic variable in the accommodation market. Therefore, our hypothesis is that **the number of times a consumer prospect uses the social connection feature**

to find a host is positively associated with the likelihood of booking and hazard rate of making the first purchase at Airbnb.

We further argue that geographic differences in the hassle savings' value of social connections. Specifically, our hypothesis that **the value of hassle savings should be larger when someone is searching internationally rather than domestically in the US since uncertainty should be higher with the former.**

Figure 3.1: Framework



Finally, we expect consumer characteristics to directly affect the consumer purchase decisions. The consumer-related variables include gender, age, signup method, number devices used for browsing, and how the consumer is acquired. Extant consumers choice literature (e.g., Guadagni and Little, 1983) suggests individual differences significantly influence consumer purchase behavior. We thus examine the effect of demographics on the consumer purchase behavior.

3.4 Data

Airbnb provides a digital marketplace for individuals to list, discover, and book unique accommodations around the world. Consumer prospects can use the web application or the android/iOS application. The dataset used in this research is available as part of the Kaggle challenge (www.kaggle.com). The dataset consists of demographics, web session records, and some summary statistics for users from the USA. The dataset specifically, contains the information for each consumer prospects such as user id, language, age, gender, date of creating the account, date of first booking, signup method - Facebook, Basic, first device type - Mac, Windows, iPhone, etc., affiliate channel. Another dataset contains information about the users' sessions such as action, action type, action detail, device type, and seconds elapsed. We selected a sample of 35,741 consumer prospects with data on all variables that we considered. For our empirical analysis, we select 4,316 consumer prospects who have used social connection feature at least once. We discuss our variables in the following section and Table 3.1 and Table 3.2 display the summary descriptive statistics for indicator and continuous variables respectively.

3.4.1 Variables

$Gender_i$ = an indicator variable set to 1 if the consumer prospect *i* is a female and 0 if the consumer prospect is male.

Age_i = a log-transformed continuous variable to represent the age of the consumer prospect *i*

$FB\_Sign\_up_i$ = an indicator variable set to 1 if the consumer prospect i uses Facebook account to sign up on Airbnb and 0 otherwise.

$Go\_Sign\_up_i$ = an indicator variable set to 1 if the consumer prospect i uses Google account to sign up on Airbnb and 0 otherwise.

Two_Device_i = an indicator variable set to 1 if the consumer prospect i uses Two different devises to access Airbnb website and 0 otherwise.

$Three\_Device_i$ = an indicator variable set to 1 if the consumer prospect i uses three or more different devises to access Airbnb website and 0 otherwise.

$Affiliate_i$ = an indicator variable set to 1 if the consumer prospect i was acquired through an affiliate website and 0 otherwise.

API_i = an indicator variable set to 1 if the consumer prospect i was acquired through Airbnb API and 0 otherwise.

$Social_i$ = a continuous variable to represent the number of times the consumer prospect i used social connection feature.

Table 3.1: Summary Statistics for Binary Variables for Proposed Sample

Variable	Proportion
Occurrence of Reservation	0.459
Female	0.466
Sign-Up: Facebook	0.611
Sign-Up: Google	0.018
Devices: Two	0.119
Devices: Three	0.009
Acquisition Channel: Search Engine Affiliate	0.047
Acquisition Channel: API Affiliate	0.110

Table 3.2: Summary Statistics for Continuous Variables for Proposed Sample

Variable	Mean	SD	Min	Max
Age	32.50	9.16	18	99
# Times Social Connections Feature Used	16.69	22.21	1	280

3.5 Methodology

The consumer prospect's decision to book an accommodation is decomposed into its two components—whether or not the purchase occurred and if one occurred, the time to purchase. The first component is modeled with a binary logit model and the second with a proportional hazards model.

3.5.1 Model Specification

The probability that consumer prospect *i* makes a purchase *t* days after she first considered is written as:

$$Lik_i = P_i(purchase) \cdot L_i(t|purchase) \tag{1}$$

The probability of occurrence of purchase is specified as,

$$P_i(purchase) = \frac{\exp(\beta X_i)}{1 + \exp(\beta X_i)} \tag{2}$$

where X_i is a vector of explanatory variables, and β is a parameter vector. Let T be a random variable that represents the time to book. Then we can write

$$T \sim Weibull(\lambda\gamma) \tag{3}$$

with $f(t)$ as the density function and $F(t)$ as the cumulative distribution function. We specify the hazard function as

$$h(t) = \lambda\gamma t^{(\gamma-1)}; \; t, \lambda, \gamma > 0 \tag{4}$$

where γ is a shape parameter and λ is a scale parameter, which is reparametrized as shown below to captures the impact of explanatory variables Y_i on the hazard rate.

$$\lambda = \exp(\varphi Y_i) \tag{5}$$

Then the log-likelihood function is given by:

$$LL = \sum \ln\left[(P_i(purchase) \cdot L_i(t|purchase))^{\delta_i} (1 - P_i(purchase))^{1-\delta_i}\right] \tag{6}$$

where $\delta_i = 1$ if consumer prospect *i* booked an accommodation and 0 otherwise.

3.5.2 Model Estimation

We obtain posterior distribution of our parameters in a Bayesian framework using JAGS (Plummer 2003). The prior specifications for the coefficients of the covariates (all β's and φ's) are normal with zero mean and large variance. The prior for shape parameter of the Weibull model is $Gamma(0.001,0.001)$. We draw two chains of 25,000 samples with random starting values for the parameters in the Markov chain. We discard the first 15,000 in each chain as burn-in and in the remaining samples; we select every 5th sample and retain 2,000 from each chain (total 4000 samples) for posterior inference. We monitor the convergence of parameters graphically and using Gelman and Rubin's potential scale reduction factor. We use the value 1.1 or lower for monitoring convergence.

3.6 Results

We estimate two different specifications to isolate the impact of social connection on the consumer purchase decision. A proposed model with social connection variable included, and a nested model which does not include the effect of social connection. We compare the model specifications based on their fit in terms of the Deviance Information Criterion (Gelman et al 2004). Model comparison results in Table 3.3 suggest that our proposed model performs better than the competing model in terms of model fit. Gelman and Rubin statistics suggest that all the parameters converged (values are less than 1.1). We next present the findings from the proposed model.

Table 3.3: Model Comparison

Model	**DIC**
No Social Connection	22949
With Social Connection	22936

3.6.1 Results of booking decision model

We estimate a binary logit model to understand a consumer prospect's intent to make a purchase. Estimates from this model presented in Table 3.4 are discussed next. The parameter estimate for Social Connection - $Social_i$ (**0.091**) is significantly, positively associated with the likelihood of purchase, indicating as consumer prospects search more times for accommodation with social connections feature, the probability of a purchase is expected to increase. This is consistent with our theory that consumer prospects reduce search costs and uncertainty with accommodations.

Other estimated parameters: Parameters related to Sign-up method Facebook, and number devices (two and three) used are significant. Specifically, the parameter related to the sign-up method - $FB\_Sign\_up_i$ (**-1.104**) is significantly, negatively associated with a purchase decision. These results suggest that compared to consumer prospects who used Direct Sign-up i.e. Airbnb account, other consumer prospects who used either Facebook account to sign-up are less likely to book an accommodation at Airbnb. Both the parameters related to the number of devices used by consumer prospects - Two_Device_i (**1.017**) and $Three\_Device_i$ (**1.105**) are significantly, positively associated with accommodation booking decision. These results are particularly interesting, as the probability of booking an accommodation at Airbnb increases as consumer prospects use greater numbers of devices.

3.6.2 Results of time to book model

We estimate a Weibull model to understand the consumer prospects' risk reduction strategies. Estimates from this model presented in Tables 3.4 are discussed next. The shape parameter is less than 1, reflecting a decreasing hazard rate over time. The coefficients of the covariates can be interpreted in a manner similar to that in a regression model (Jain and Vilcassim 1991). A positive (negative) coefficient means that the rate of booking increase (decrease) as covariate Y_i increase i.e. time to booking decreases.

The parameter for social connection variable (**0.050)** suggests that the number of times the consumer prospect uses the social connection feature is positively significantly associated with hazard rate. This result suggests that consumers rely on social connections to reduce perceived risk, which reduces the time taken to book an accommodation. This is consistent with our theory that consumer prospects reduce time to purchase by using social connection feature to search for accommodation.

Table 3.4: Parameter Estimates for Proposed Model

Variable	**Time to Reservation**		**Likelihood of Reservation**	
	Mean	**SD**	**Mean**	**SD**
Constant	**-1.853**	0.341	0.208	0.462
Female Vs Male	-0.051	0.047	-0.002	0.065
Log(Age)	0.044	0.095	-0.001	0.129
Sign-Up: Facebook Vs Airbnb	**-0.098**	0.046	**-1.104**	0.068
Sign-Up: Google Vs Airbnb	-0.152	0.157	-0.200	0.232
Devices: Two Vs Single	**0.663**	0.067	**1.017**	0.116
Devices: Three Vs Single	**0.805**	0.200	**1.105**	0.394
Acquisition Channel: Search Engine Affiliate Vs Direct	0.149	0.099	0.240	0.187
Acquisition Channel: API Affiliate Vs Direct	0.008	0.085	-0.071	0.105
Log(# Times Social Connections Feature Used)	**0.050**	0.019	**0.091**	0.027
Shape Parameter	**0.472**	0.008		

Bold: 95% credible intervals exclude zero.

Other estimated parameters: Parameters related to Sign-up method Facebook, and number devices (two and three) used are significant. Specifically, the parameter related to the sign-up method - $FB\_Sign\_up_i$ (**-0.098**) is significantly, negatively associated with hazard rate. This result suggests that compared to consumer prospects who used Direct Sign-up i.e. Airbnb account, other consumer prospects who used Facebook account to sign-up are expected to take more time to book an accommodation at Airbnb. Both the parameters related to the number of devices used by consumer prospects - Two_Device_i (**0.663**) and $Three\_Device_i$ (**0.805**) are significantly, positively associated with hazard rate. These results are particularly interesting, as the time taken to make a purchase at Airbnb is reduced as consumer prospects use greater numbers of devices.

Figure 3.2: Observed and Predicted Probability of Purchase
by # Times Social Connections Feature Used

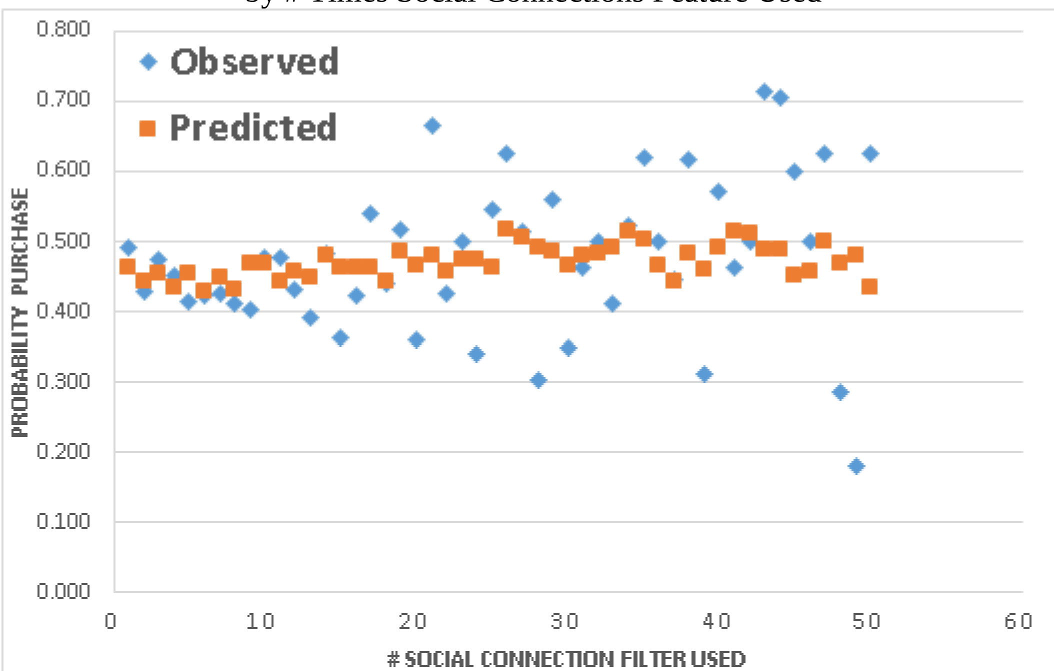


Figure 3.3: Change in Likelihood

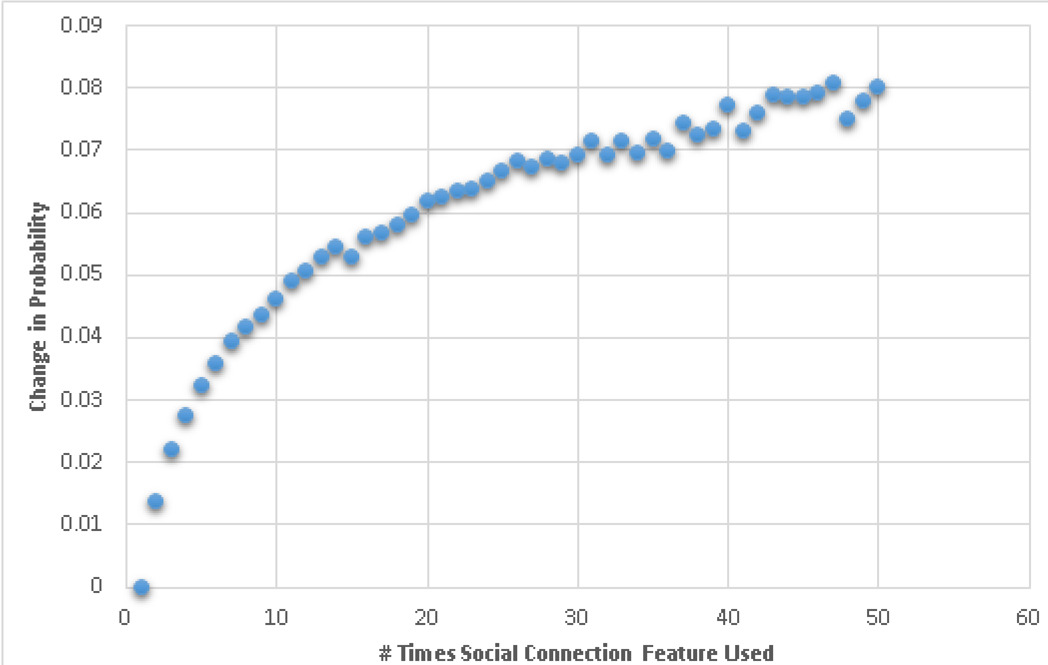
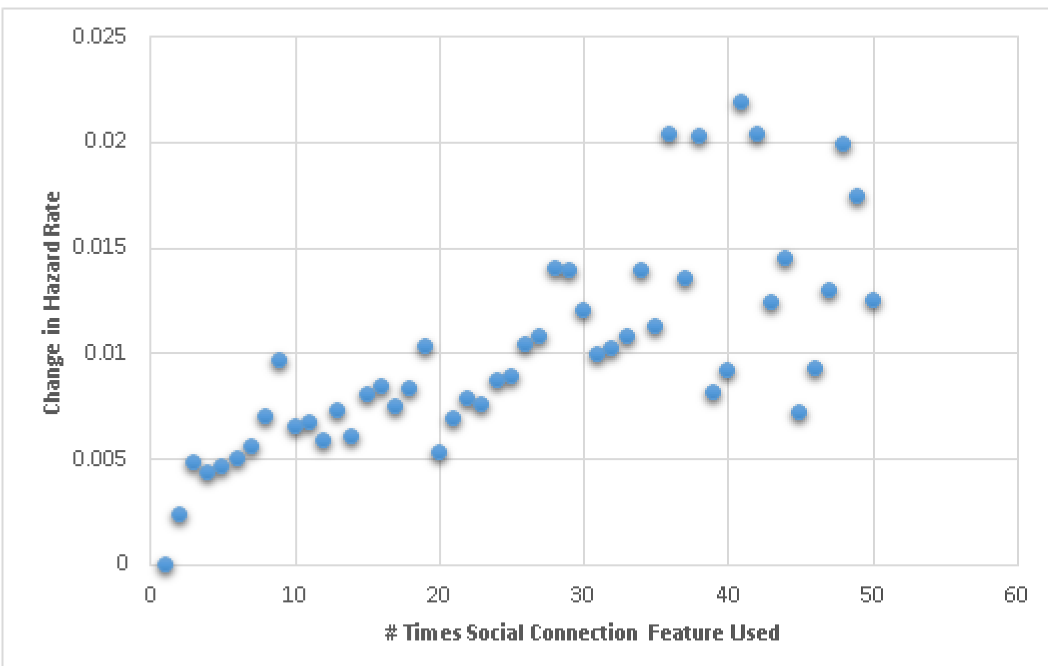


Figure 3.4: Change in Hazard rate



3.7 Robustness Checks

3.7.1 Endogeneity of Social Connections

The social connections variable could, however, be endogenous with search time. Those who have friends on Facebook may be more experienced online users and hence, faster in searching and more willing to purchase, online. Additionally, they may be using the social connections feature only because it allows them to see which of their friends may be hosts or had used accommodations they are also considering. While field experiments (randomizing the sample) can be a way to avoid such endogeneity, propensity score matching (PSM) can always attenuate such endogeneity (Li & Kannan, 2014; Kannan, Reinartz, & Verhoef, 2016).

We use propensity score matching with visitors who use the social connections feature on Airbnb as the treatment group matched with those who do not use this feature and re-estimate my models on the pooled sample. We use the signup method, which indicates whether people used Facebook/Google to set up an account on Airbnb before searching for accommodations. We also use age as a matching variable as a proxy for experience with- and interest in- using social media and learning about friends' activities. Thus, the selected matched sample includes 4,316 consumer prospects who have used social connection feature at least once and 4,316 consumer prospects who have never used. Table 3.5 and Table 3.6 display the summary descriptive statistics for indicator and continuous variables respectively. Results (Table 3.7) from this re-estimation are consistent with my findings and indicate that social connections are indeed reducing search time and increasing the likelihood of a purchase.

Table 3.5: Summary Statistics for Binary Variables for Matched Sample

Variable	**Proportion**
Occurrence of Reservation	0.475
Female	0.496
Sign-Up: Facebook	0.619
Sign-Up: Google	0.011
Devices: Two	0.120
Devices: Three	0.006
Acquisition Channel: Search Engine Affiliate	0.189
Acquisition Channel: API Affiliate	0.094

Table 3.6: Summary Statistics for Continuous Variables for Matched Sample

Variable	**Mean**	**SD**	**Min**	**Max**
Age	32.38	9.17	18	99
# Times Social Connections Feature Used	7.36	17.36	0	280

Table 3.7: Parameter Estimates for Robustness Check – Model 1

Variable	Time to Reservation		Likelihood of Reservation	
	Mean	**SD**	**Mean**	**SD**
Constant	**-1.551**	0.262	**1.144**	0.320
Female Vs Male	**-0.105**	0.032	-0.034	0.046
Log(Age)	0.025	0.074	**-0.189**	0.090
Sign-Up: Facebook Vs Airbnb	**-0.128**	0.032	**-1.097**	0.048
Sign-Up: Google Vs Airbnb	**-0.288**	0.144	-0.391	0.212
Devices: Two Vs Single	**0.405**	0.043	**0.690**	0.072
Devices: Three Vs Single	**0.491**	0.163	**0.823**	0.295
Acquisition Channel: Search Engine Affiliate Vs Direct	**0.086**	0.040	0.088	0.060
Acquisition Channel: API Affiliate Vs Direct	-0.122	0.066	**-0.214**	0.083
Social Connections Feature Used Vs Not Used	**0.003**	0.001	**0.003**	0.001

Bold: 95% credible intervals exclude zero.

3.7.2 Geographic Differences

We exploit possible geographic differences in the hassle savings' value of social connections to validate our findings. Specifically, we hypothesize that the value of hassle savings should be larger when someone is searching internationally rather than domestically in the US since uncertainty should be higher with the former. We operationalize demographic variable, $Dest_i$ as an indicator variable, and we set to 1 if the consumer prospect i booked an accommodation in the domestic market and 0 if it is from a foreign market. We, therefore, re-estimate my model with geographic-specific estimates of the effects of social connections. We do find (Table 3.8) that the effects are larger both on the time to make the first purchase and on the likelihood of the first purchase for international listings than domestic ones.

Table 3.8: Parameter Estimates for Robustness Check-Model 2

Variable	**Time to Reservation**		**Likelihood of Reservation**	
	Mean	**SD**	**Mean**	**SD**
Constant	**-1.811**	0.324	0.190	0.465
Female Vs Male	-0.051	0.046	-0.001	0.065
Log(Age)	0.032	0.091	0.004	0.130
Sign-Up: Facebook Vs Airbnb	**-0.099**	0.048	**-1.103**	0.068
Sign-Up: Google Vs Airbnb	-0.154	0.156	-0.197	0.234
Devices: Two Vs Single	**0.664**	0.068	**1.019**	0.119
Devices: Three Vs Single	**0.797**	0.196	**1.104**	0.394
Acquisition Channel: Search Engine Affiliate Vs Direct	0.149	0.100	0.242	0.182
Acquisition Channel: API Affiliate Vs Direct	0.012	0.086	-0.074	0.108
Log(# Times Social Connections Feature Used)				
Pooled			**0.092**	0.027
Domestic Reservation	**0.045**	0.021		
Foreign Reservation	**0.058**	0.025		

Bold: 95% credible intervals exclude zero.

3.8 Discussion

Consumers are increasingly purchasing accommodation services through sharing economy platforms such as Airbnb as they grow in popularity. It is critical therefore for SEP's to understand how consumers who have never used accommodation services to make their first purchase. Consumers are uncertain about the features and quality of accommodation, and this is expected to very high for first-time consumers. A source that sharing economy providers have been offering is information on whether the host or any previous renters of a shared accommodation are acquaintances of a prospective renter. Airbnb, for instance, offers this through a feature called *social connections* that allows visitors to see only those accommodations reviewed by their friends or friends of friends on Facebook. The feature thus provides *hassle savings* by reducing search costs and can, therefore, be a strategic variable in the accommodation market. In this research, we investigate the time taken to make the first purchase from when the Airbnb service is first considered by the consumer prospect including the extreme case of infinite time meaning that the choice never occurs. Our findings indicate a significant effect of social connections provide hassle savings to consumers in reducing the time to and increasing the likelihood of, the first purchase.

3.8.1 Managerial Implications

Findings provide insights into how sharing economy platforms by using social connections feature can shorten the time taken by prospective customers to make their first purchases through the platforms. For example, consumers prospects now have a more personal way to search for unique accommodations around the globe on AriBNB. With over million nights booked through Airbnb to date, chances are someone a consumer know has already used Airbnb. On top of being able to search for accommodation that friends or someone in the network have reviewed, Social Connections also allows people to find unique places to rent from hosts who are direct friends, friends of friends, or share similar affiliations. Hotels also can implement such a feature to be competitive. Social connections can be used as a strategic variable to provide consumers hassle savings by reducing search costs and uncertainty.

3.8.2 Limitations and Future Research

Though we provide insights into how consumers of Airbnb or other service providers can benefit by providing information through social connection feature to reduce uncertainty, we acknowledge two main limitations of this study. First, we focused mainly on consumer prospects. However, findings from existing customers purchase behavior or usage of social connection feature is also important to generalize the findings. Second, we did not include other uncertainty reduction strategies such as reading reviews by other customers. Therefore, future studies can incorporate data from existing customers and other variables into analyses.

Though we provide some insights on how consumer prospects reduce uncertainty and make their first purchase on Airbnb, there are several avenues for additional research in this area. For instance, the role of uncertainty in consumer choice between LP's such as Hotels and SEP's such as Airbnb. How providers' content like photos or videos of the services can reduce uncertainty is another such avenue.

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Appendix 3A

A guest seeking to rent a room or property on Airbnb can enter the desired destination (e.g., destination, city, address etc.,), dates (Check In and Check Out), and number of guests (e.g, Adults, Children, and Infants) then view a variety of options including room type (Entire home, Private room, or Shared room), other property features and characteristics, price, and availability. Figures 3A.1-3A.3 present screenshots of key steps in the search process, including initial listings (1), main search (2), search filters, (3) property listing, and (4) a listing details including listing details, host photo and name, and reviews from prior guests. To book a room or property, the guest uses Airbnb's request and payment systems: Airbnb presents the guest's request to the host who accepts or rejects, and if the host accepts, Airbnb charges the guest and pays the host accordingly.

Figure 3A.1

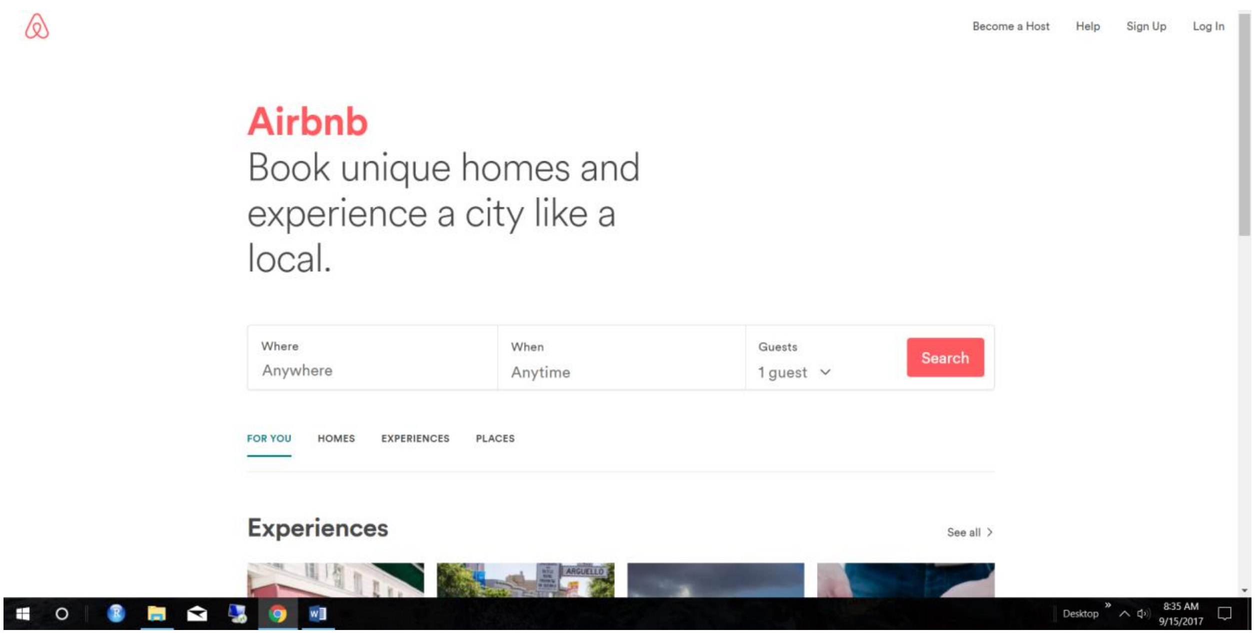


Figure 3A.2

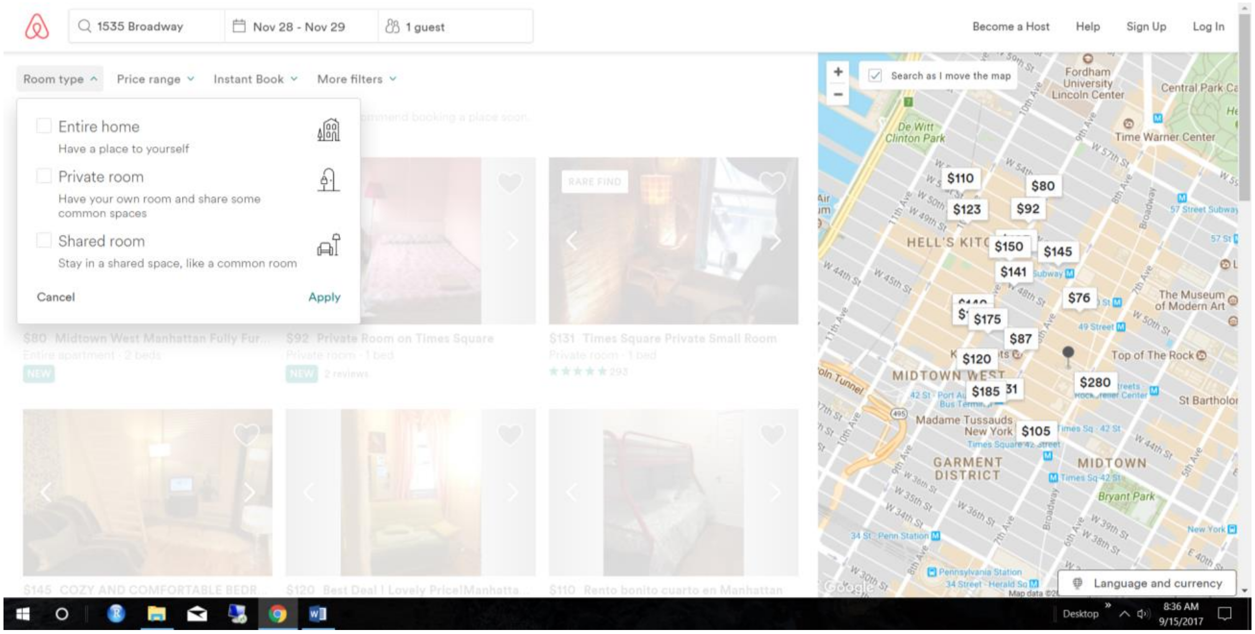


Figure 3A.3

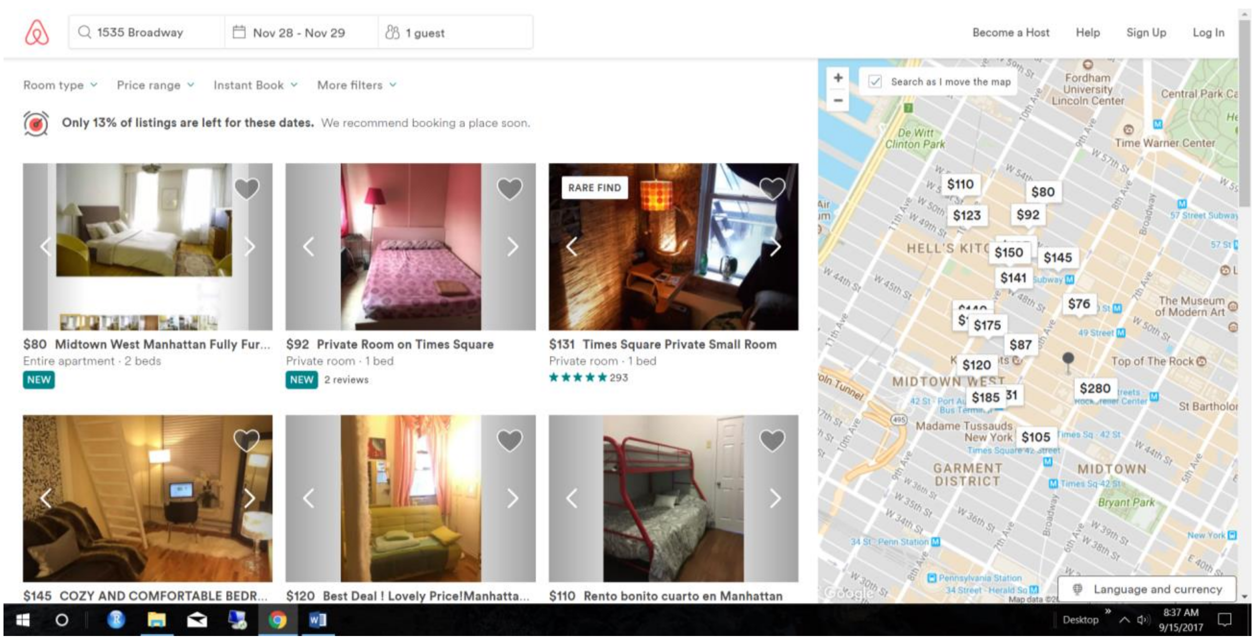
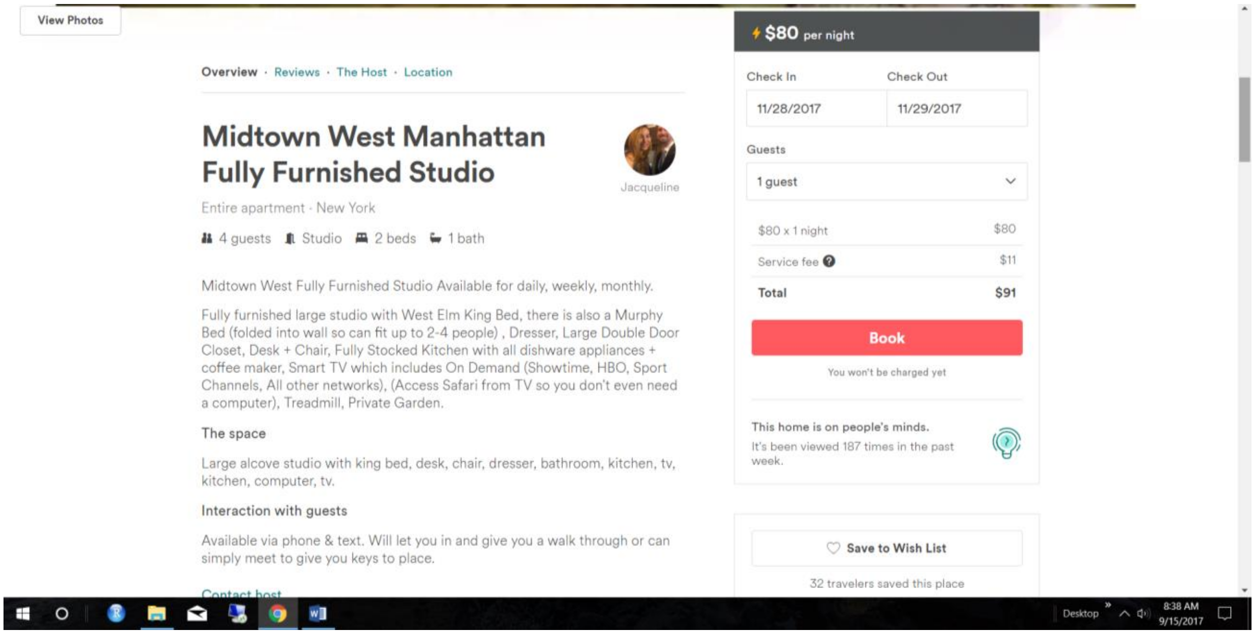


Figure 3A.4


View Photos
Overview · Reviews · The Host · Location
Midtown West Manhattan Fully Furnished Studio
Jacqueline
Entire apartment · New York
4 guests Studio 2 beds 1 bath
Midtown West Fully Furnished Studio Available for daily, weekly, monthly.
Fully furnished large studio with West Elm King Bed, there is also a Murphy Bed (folded into wall so can fit up to 2-4 people) , Dresser, Large Double Door Closet, Desk + Chair, Fully Stocked Kitchen with all dishware appliances + coffee maker, Smart TV which includes On Demand (Showtime, HBO, Sport Channels, All other networks), (Access Safari from TV so you don't even need a computer), Treadmill, Private Garden.
The space
Large alcove studio with king bed, desk, chair, dresser, bathroom, kitchen, tv, kitchen, computer, tv.
Interaction with guests
Available via phone & text. Will let you in and give you a walk through or can simply meet to give you keys to place.
$80 per night
Check In
Check Out
11/28/2017
11/29/2017
Guests
1 guest
$80 x 1 night $80
Service fee $11
Total $91
Book
You won't be charged yet
This home is on people's minds.
It's been viewed 187 times in the past week.
Save to Wish List
32 travelers saved this place
Desktop
8:38 AM
9/15/2017

Appendix 3B

Figure 3B.1

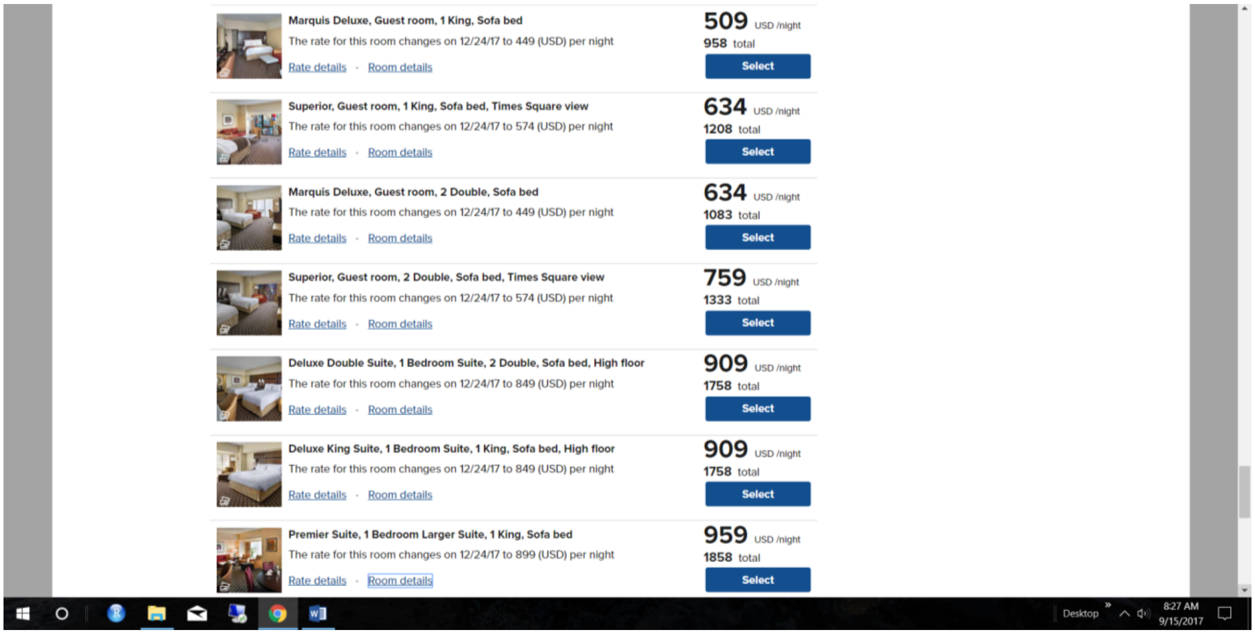
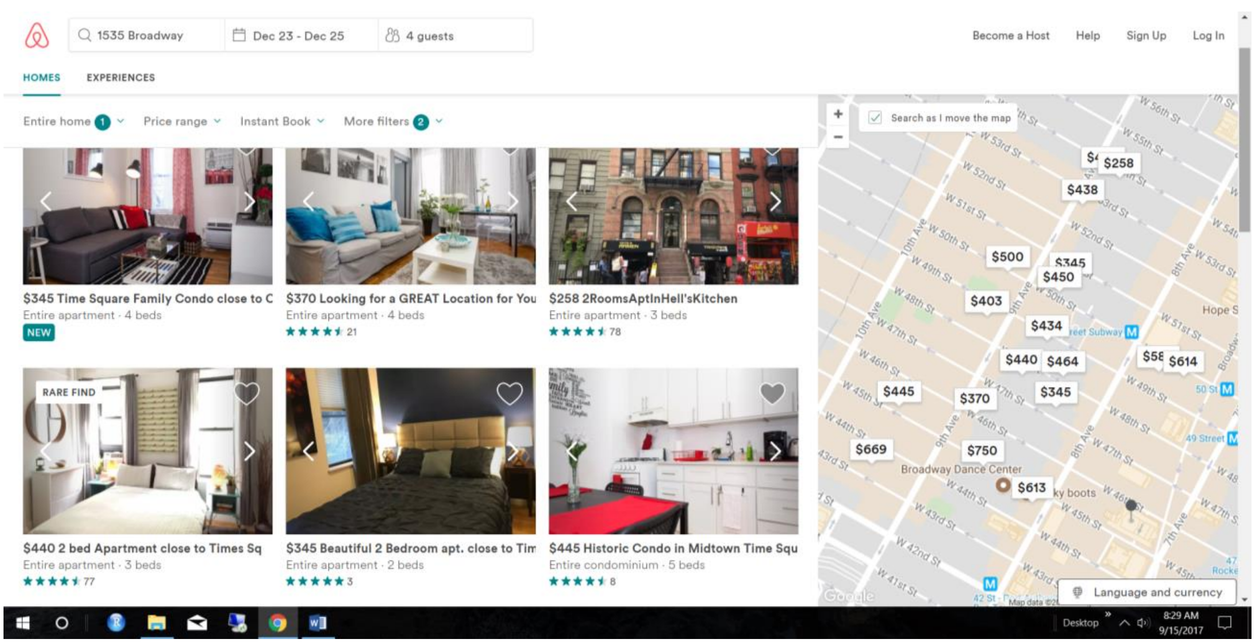


Figure 3B.2



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