Search Frictions and the Design of Online Marketplaces

Job Market Paper: Preliminary

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I use data on searches and transactions in an online marketplace to study market efficiency and policy. The setting of this paper is Airbnb, a prominent online marketplace for short-term housing rentals. Search on Airbnb occurs when potential guests browse the website and send inquiries to hosts about rooms to stay in. Despite the substantial reduction in search costs due to the marketplace, only 48% of searchers who send inquiries eventually match. I build a model with directed search, heterogeneous agents, and multiple search frictions to explain the match rate and other market outcomes. I find that if search frictions were removed, there would be 78% more matches in the marketplace and that host revenue would increase by $62 per searcher. I study a set of policies aimed at reducing the impact of search frictions. Of these policies, personalized ranking algorithms lead to the biggest improvement, increasing the match rate by 7% over the baseline. Finally, I show that the A/B search experiments favored by internet platforms overstate these improvements by more than 90%.

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1. Introduction

The internet has transformed how consumers search for jobs, apartments, spouses, and consumer products. In this paper, I use detailed data on searches and transactions from a prominent online housing platform to analyze the efficiency of online search. In the process, I document and quantify several distinct frictions, each of which appears in the theoretical literature. These include the fact that consumers cannot consider all options available, that sellers may not be willing to transact with all potential buyers, and that markets with bilateral trades may suffer from congestion. I build an empirical model that combines these mechanisms and use it to study platform changes aimed at improving search efficiency. I show how better search ranking algorithms improve outcomes, and why these improvements are overstated by the A/B search experiments favored by internet platforms.

This paper contains three main quantitative results. First, while online platforms presumably make matching more efficient, frictions still play an important role. I find that there would be 78% more matches and revenue per searcher would be $62 higher without frictions. Even without frictions, only 48% of searchers would transact because there is a limited amount of supply in the market. Second, I find that two mechanisms, the lack of knowledge about which seller is willing to transact and incomplete information about the full set of options in the market, explain most of the inefficiency in the market. Third, I use the model to show that personalized ranking algorithms increase the match rate by 7%. However, policies that increase the intensity of search or reduce congestion have a minimal impact on market outcomes. Furthermore, because there are supply constraints in the market, search experiments overstate the true effect of better ranking algorithms by more than 90%.

The setting of this paper is Airbnb ("Airbed and Breakfast"), a rapidly growing online marketplace for housing rentals that has served over 9 million guests between 2008 and late 2013. Airbnb provides a platform for individuals to temporarily rent out an unused room or property to travelers.[1] Search on Airbnb begins when potential guests submit their trip details, which consist of a city, dates of stay, and number of guests, into a search engine. The search engine returns a set of listings in that city. If a listed option is appealing, the searcher sends an inquiry to the host of that listing. An inquiry typically asks about the availability of the place and other additional details. The host can respond to an inquiry by stating that the place is available, unavailable, or by asking a question. The host's response is indicative of a complex decision to let a stranger stay at her place. This decision combines issues of trust, availability, hassle and the possibility of better offers.

[1] Similar marketplaces to Airbnb exist in industries such as contract labor (Odesk, Freelancer and Taskrabbit), dating (OkCupid, Match.com and eHarmony), craft goods (Etsy and Ebay) and private transportation (Uber and Lyft).

Airbnb is an excellent environment for studying search and matching frictions for several reasons. First, as in the labor and dating markets, there are many heterogeneous options and both sides of the market have heterogeneous preferences. Second, because hosts can only accommodate one trip for a set of dates, there is a potential for large congestion frictions. Burdett, Shi and Wright (2001) show that markets where sellers have limited capacity (such as Airbnb, the dating market, and the housing market) are characterized by different matching functions than settings where sellers have a large capacity such as the college admissions market. Lastly, the Airbnb dataset is one of the few research datasets that contains data on search, communication, and match outcomes. Importantly, I can classify the text of a host's response as a rejection or a non-rejection. This type of information is crucial in interpreting whether a transaction failed due to the searcher or due to the seller. Analogous data in the labor market would contain resume submissions, interview invitations, and interview outcomes at a searcher-vacancy level.

I use the data to estimate models of directed search and screening separately before combining them into a simulation of market outcomes. Searchers in the model send inquiries conditional on a set of properties seen while browsing the website. I first specify a process by which the listings that are more likely to be seen by searchers in the data are also more likely to be considered by searchers in the model. After browsing the website, searchers choose which properties to contact according to a discrete choice model. The searcher's utility for a particular listing is a function of characteristics such as location, size, and price. As in Hitsch, Hortacsu and Ariely (2010), the demand of searchers also depends on the match between searcher and listing characteristics. For example, searchers for trips with more guests prefer bigger properties.

Upon receiving an inquiry, hosts choose whether to reject or accept a potential guest. Rejection by hosts happens in 49% of all inquiries. There are three distinct causes of rejection in my model: screening, congestion, and "stale" vacancies. Screening occurs when a host rejects a searcher because of the searcher's personal or trip characteristics. For example, some hosts may not be comfortable sharing a space with an individual who has no reviews. To capture the host's decision process, I estimate a logit model of a host's propensity to screen a guest as a function of guest and host characteristics. Congestion occurs when a searcher sends an inquiry to a listing that is about to transact with another searcher. Congestion arises in my model because it takes time for transactions to clear. Lastly, stale vacancies occur when a listing which is not actually available for a given week is nonetheless visible in search and contacted. In my dataset, over 20% of communications are screened, over 21% are sent to stale vacancies and less than 6% are affected by congestion. This result is interesting because much of the theoretical literature on directed search such as Kircher (2009), Albrecht, Gautier and Vroman (2006) and Burdett, Shi and Wright (2001) has focused on congestion as the main cause of rejection

[1]The sampling procedure is similar to the one used by Dinerstein et al. (2013) for search on Ebay.

in search markets.[2][3]

I combine the estimated search and screening models into a simulation of how the market clears over time. In the simulation, searchers enter Airbnb looking for a place to stay in a given week and market and conduct search according to the directed search model. Inquiries sent by the searchers are either accepted or rejected by hosts according to the reasons above. If a guest chooses to book a property, the transaction takes time to clear. Additional searchers enter the market sequentially and send inquiries. The actions of searchers and hosts then generate the aggregate matching and rejection probabilities. I calibrate parameters in the model to match the propensity of searchers to send multiple inquires, and the level of congestion in the market. The calibrated model comes within several percentage points of matching the empirical booking rates, contact rates, and the frequency of rejection even though these moments were not used in the calibration. I simulate the model without frictions in order to determine the potential of policy to improve outcomes. I find that there would be 21% more matches and $62 greater host revenue per searcher than in the baseline scenario.

Because search frictions are large, marketplace policy can potentially improve outcomes. The policy space for online marketplaces encompasses search ranking, site layout, new matching mechanisms and explicit rules that affect the behavior of agents. Most marketplaces rely on experimentation to learn about the effect of a particular policy. However, experimentation is of limited use within marketplaces for three reasons. First, estimated treatment effects from searcher level experiments can be biased. The market level effect of a policy can differ from the individual effect because whenever a searcher books a room, other searchers cannot book the same room. Therefore, a treatment that helps the treated also makes the control group worse off. Second, the parameter space of possible marketplace policies is too large to explore with experimentation alone. For example, a ranking algorithm that uses machine learning might have thousands of parameters. Lastly, the effect of policies depends on time-varying market conditions such as the number of agents in the market and the ratio of searchers to sellers. An experiment, on the other hand, is typically run in a specific time period and set of markets. Understanding how market conditions affect outcomes can inform experimental design and can help the market designer adapt policies to different situations.

I use the model to simulate Airbnb with alternate search rankings, search propensities, and levels of market tightness. A policy that improves the listings displayed on the website by using estimates of agents' utilities improves matching probabilities by 7%. However, the effectiveness of the policy depends on market conditions. For example, if there had been 50% fewer searchers and listings in the market then the treatment effect

[3] Although see Chade, Lewis and Smith (2013) for an example where college applicants do not know which college will accept them.

[3] Stale vacancies are similar to congestion from the perspective of the searcher but are generated by a different seller behavior.

of the policy would be less than half the size. Furthermore, as the platform's model of searcher behavior becomes more predictive, policy comes closer to achieving the frictionless benchmark.

The approach taken in this paper differs from the aggregate matching function approach used in many papers on search markets (Petrongolo and Pissarides (2001)). In aggregate matching functions the number of potential matches given a set of searchers and vacancies is determined by a matching technology which is not, in general, based on micro-foundations. The lack of micro-foundations makes aggregate functions unsuitable for studying policies, technologies, and changes in market structure which affect the matching process. For example, Lagos (2000) derives a micro-founded aggregate matching function for the taxicab market and shows that its shape will be sensitive to policy. Similarly, policies in my model change the relative contribution of searchers and sellers in the matching function, as well as the overall returns to scale. I show that a better ranking algorithm increases the weight on hosts in the matching function and that this algorithm has a greater effect in a thicker market. Further, I find that aggregate matching on Airbnb has increasing returns to scale because larger markets create larger consideration sets for searchers, leading to better matches and more inquiries.

The paper is organized as follows. Section 2 gives more detail about Airbnb. Section 3 describes the model of directed search and section 4 describes the determinants of rejection. Lastly, section 5 describes the model and shows the empirical results.

2. Data and Setting

2.1. Airbnb Background

Airbnb describes itself as a trusted community marketplace for people to list, discover, and book unique accommodations around the world − online or from a mobile phone.[4]. It is a fast-growing startup that was founded in 2008 and that has more than doubled the number of guests accommodated in every year of its operation. In 2012, Airbnb accommodated over 3 million guests and listed over 180 thousand new listings. It has listings in more than 34 thousand cities worldwide and is available in more than 30 languages.

Airbnb has created a market for a previously rare transaction: the rental of an apartment or part of an apartment in a city for a short term stay by a stranger.[5] These transactions were not occurring previously because there were large costs to securely exchanging money, communicating with strangers and evaluating a stranger's trustwor-

[4] https://www.Airbnb.com/home/press

[5] Couchsurfing, a large travel based social network started in 2003, facilitates similar stays but without monetary exchange. Craigslist has listed sublets and short-term vacation rentals since the late 1990's. Vacation rentals by owners in tourist towns have also existed for a long time.

thiness. Airbnb was one of the first platforms to provide a set of tools and services which enabled guests and hosts to arrange stays in a relatively risk-free manner. These tools are important because hosts on Airbnb are typically non-professionals, over 80% of whom list just a single room or property.

In a typical Airbnb transaction, guests and hosts have the ability to inconvenience each other by being disruptive or by lying about the characteristics of a room or trip. Communication occurs on the platform both to screen counter-parties and to cement the details of the trip such as the key exchange and check-in times. Importantly, hosts are allowed to deny potential guests for any reason. Guests and hosts have the opportunity to review each other after the trip. In subsection 3.2, I show that the stock of reviews on the site provides important information and affects both host and guest behavior.[6] Users of Airbnb can disclose information about themselves through photographs and textual descriptions. Airbnb also provides free professional photography services to hosts and verifies users' identity using online social networks (Facebook, LinkedIn, and Twitter) and passports or driver's licenses.[7] In the empirical section I show that this information is important in the decisions of agents on Airbnb.[8]

The payments mechanism on Airbnb is a big innovation compared to previous platforms for accommodations such as Craigslist, where payments were handled offline. The marketplace holds payments in escrow until the stay has happened in order to prevent fraud. The escrow service allows Airbnb to resolve disputes between guests and hosts and to enforce the payment of security deposits and cancellation penalties. Airbnb also offers a one million dollar insurance guarantee against major damage done to properties by guests. Airbnb generates revenue by taking a percentage fee of every transaction that takes place on the platform. Hosts typically have a 3% fee while guests have a variable fee that ranges between 6% and 12% depending on the details of the transaction.

Another important service that Airbnb provides is the management of pricing and property calendars. For each date, each listing has a binary availability that is displayed on the site. If a booking occurs, a host's calendar is automatically blocked off for the dates of the trip. Alternatively, the host can manually update the calendar to be unavailable for a set of dates. In either case, the property can no longer be booked and will not show up in search for the blocked off dates. Hosts might not update their calendars even if they are unavailable because they are uncertain about future availability, want to see potential guests or face updating costs. As a result, potential guests send inquiries to seemingly available listings which are actually off the market.

[8] There is a literature that documents the importance of reviews in a variety of online platforms. For example, Pallais (2013) shows that reviews are valuable and under-provided on Odesk, a labor market platform.

[8] For more details see: http://blog.airbnb.com/introducing-airbnb-verified-id/

[8] Lewis (2011) shows that information voluntarily disclosed by sellers on Ebay Motors affects market prices.

2.2. The Booking Process

There is a set of discrete steps that lead to booking a room.

1. Structured Search (Figure 1) - Searchers enter the travel dates, number of guests and location into a search engine and receive a list of results. The search can then be refined using filters, maps and sorting.

2. Investigation (Figure 2 and Figure 3) - The searcher clicks on a listing in search. The subsequent page displays additional photos, amenities, reviews, responsiveness, house rules and information about the host.

3. Message (Figure 4) - The guest sends messages to hosts inquiring about room details and availability. A host can respond by saying that the room is unavailable, that the room is available or by asking a follow up question. The host might also not respond at all. A guest may send multiple inquiries both initially and after receiving responses.

4. Booking - If a transaction is agreed upon, the guest can click the "Book It" button. If the host accepts, the money is charged and taken in escrow by the platform. Some transactions occur without a messaging step if the host allows the "Instant Book" feature.

5. Stay - After a trip is booked, there is further communication needed to exchange keys and coordinate the details of the trip. Either side can cancel with a pre-specified penalty rate.

2.3. Data Description

My datasets are composed of the full set of inquiries and transactions that occurred in major US markets on Airbnb. For tractability, subsamples of the entire set of the data are used in the various sections of the paper. In this section, I narrow my data set to comprise all contacts to US markets which occurred for trips starting in 2012, while in the model sections I focus on one market and a narrower set of dates. For each communication I observe the time a message was sent, who sent the message, who received the message and the content of the message. Each set of messages between a guest and a host is aggregated into a "thread" that contains information about trip dates, the number of guests and the room of inquiry.

I group each set of communications in my dataset by search spell (alternatively referred to as a trip attempt). A search spell is defined as a set of inquiries and transactions pertaining to a stay by a specific guest in a specific market and in a specific week of the start of the trip. For each searcher, I observe the number of reviews, the number of pictures, demographics and other characteristics. For each property I observe the listed price, number of reviews, review score, location, number of pictures and other characteristics at any point in time.

There are some unavoidable limitations to the dataset. Firstly, I do not always observe the correct price in cases when a host changes prices for a specific date over time. The reason for this is that the data on date specific pricing is from monthly snapshots rather than from daily snapshots. This is not a major problem because most hosts do not even set date specific prices and instead use a calendar wide listed price. Further, I do not observe the entire path of availability in the market. For example, a property might initially be available for a given week, then become unavailable and then become available again. In that case. I treat that property as always being available. Lastly, some of the observed characteristics such as age and gender are either missing or entered inaccurately by users.

2.4. Identifying Host Rejections

The meaning of textual data must be derived before the data is useful for empirical work in economics. There is no complete classification of communications between searchers and sellers into an ontology because communication is ambiguous and serves many purposes. I identify the most important bit of information: whether a host's response to a guest indicates that the host is interested in the transaction. For example, the response "Sorry, the place is unavailable." should be classified as a rejection whereas the response "Yes it is available. Go ahead and book it." should be classified as a non-rejection.

I use several approaches to determine whether a response is a rejection. If an inquiry led to a booking or was labeled as accepted by the host then it is classified as "not rejected". If a response was labeled by the host as a rejection or if there was no response within a week then the response is classified as a rejection.

If the response does not fit into any of the above categories, a text classifier is applied to the first (or in some cases second) response by a host to a guest. I use a common technique in natural language processing called a regularized logistic regression to classify text (see Appendix A for details). I combine the text classification with cases when the response is discernible through other methods.[9]

In total, 49% of all inquiries were rejected. Of all responses classified as rejections, 37% were non-responses, 30% were classified by the host, and 32% were classified the regularized logistic regression.

2.5. Descriptive Evidence About Rejections

Communication on Airbnb frequently fails to result in a transaction. For US Markets in 2012, just 15% of inquiries and 48% of search spells transact. In this section, I provide descriptive evidence that matching frictions are indeed large and prevalent across Airbnb and that there are likely to be unrealized matches because guests tend to leave after a rejection.

[9]Foreign language responses are removed from the analysis.

A searcher chooses how intensely to search in a given search spell. An inquiry is considered simultaneous if it is sent within the first two hours of the first inquiry being sent. Any search that does not occur soon after the first inquiry is considered sequential because the host's response or lack thereof provides additional information to the searcher. Of all search attempts, 70% begin with only one initial inquiry.

Figure 5 displays the set of potential outcomes for those search spells. Conditional on the initial inquiry not being rejected, a search spell results in a transaction 65% of the time. However, if the initial inquiry is rejected, searchers leave Airbnb without an additional inquiry 62% of the time. Even if the searcher partakes in sequential search by sending additional inquiries, she only books 41% of the time.

The above analysis does not control for guest, trip and market characteristics. Table 1 shows the results of a linear probability model where an indicator for whether an inquiry for successful booking is regressed on whether the first inquiry was rejected. Rejection is associated with a 50% decrease in the probability of eventually booking and stays similar in magnitude after adding controls for market, week and trip characteristics. My model explains how this effect emerges in equilibrium due to the timing of inquires and the preferences of guests and hosts.

3. Search Behavior

3.1. Consideration Set Formation

Potential guests on Airbnb search for a place to stay by entering a location, a set of dates and the number of guests. For each query, the search engine returns a set of 21 listings according to a ranking algorithm. The algorithm generates a score that is a function of the distance of a listing from the query parameters and the quality of the listing's characteristics. Listings are then ordered according to their scores. The guest interacts with the search engine using a combination of additional search terms, filters, maps and sorting. Searchers do not see all listings because there are typically thousands of available listings for major US markets.[10] Some properties are more likely to be sampled due to the search algorithm and the preferences of searchers. The probability with which a listing is sampled also depends on what other listings are still visible in the market. In this section, I describe a simple empirical model that captures these aspects of consideration set formation.

A model of browsing is needed for three reasons. First, I need to be able to simulate consideration set under counter-factual policy regimes. Second, it is almost impossible to exactly recreate the ranking algorithm used on the site because each ranking is determined

[10] Searches in October of 2013 for stays in New York, Seattle, San Diego, Austin, Los Angeles, Chicago, Miami and many other cities resulted in more than 1000 search results.

according to a complex and poorly documented set of transformations of listing specific variables. Further, the product of these transformations is weighed against query specific parameters such as the exact location at which the map is centered and filters that the searcher uses. Lastly, even if I was able to exactly replicate the ranking algorithm used on the site, I would still need to model the filter usage of searchers. The complexity of browsing behavior is a general problem for analyzing search data from the Internet.

In the model, searchers browse a random subset of all visible listings in the market. This subset is drawn at according to a set of sampling weights. The sampling weight of each listing, ω_h, is determined according to the following transformation (Dinerstein et al. (2013)):

$$\omega_h = e^{\gamma^{\frac{w_h - w_{min}}{sd(w_h)}}} \tag{1}$$

where w_h represents the propensity of a listing, h, to be seen based on observed characteristics, w_{min} is the minimum of w_h over all listings and γ is a parameter that governs the degree to which the consideration sets of searchers are correlated with each other. w_h is determined according to the following estimation equation.

$$h_{seen,g} = 1(X_h'\mu + \gamma_g + \epsilon_{gh} > 0) \tag{2}$$

where h denotes a listing, seen indicates whether the listing was seen by searcher g, X_h are listing characteristics, γ_g is a guest specific fixed effect and ϵ_{gh} is a logit error term. I set w_h be the predicted logit index: $X_h'\hat{\mu}$ resulting from the above regression. This specification captures the fact that certain features such as reviews and location make some listings more likely to be seen than others.

The estimating sample for Equation 2 is a random set of searchers in a large U.S. city (referred to as City X from now on). Each listing which could have been seen by a searcher is matched to its characteristics at the time of the search. The procedure for computing sampling weights consists of two steps. In the first step, I estimate a conditional logistic regression that predicts which listings are seen by searchers out of all the listings that could have been seen using listing characteristics. In the second step, I transform the w_h according to Equation 1. The correlation parameter γ is calibrated so that the matching model matches the level of congestion in the market. The total number of properties seen by a particular searcher is drawn according to an exponential distribution with mean equal to the mean number of listings seen in the demand estimation sample. The calibration is discussed in section 5.

For the purpose of the of the simulation, I assume that the sampling probabilities are independent of preferences. In practice, the consideration set might actually be correlated with preferences. I discuss how this assumption affects the model generated

[10]See Appendix B for estimates.

policy experiments in section 5. Further, I have not explicitly modeled the effect of the order in which listings appear on a given page. There is a growing literature that examines the effect of the search order on advertising clicks, movie viewing decisions, and other search behavior.[11] However, because ranking data is poorly logged in my sample, I do not include ranking in the analysis.

3.2. Directed Search and Preferences

The guest's choice of which property to contact from a given consideration set is determined by a random utility discrete choice model. The property characteristics visible in search results are price, location, number of reviews, property type and any common social connections between the guest and host. Other features, which are visible upon further inspection, include additional pictures of the property, a free form textual description of the property, the text of listing reviews, a description of the host, average response time, average response rate, frequency of calendar update, security deposit, bedrooms, bathrooms and cancellation policies. The searcher weighs these characteristics and chooses one (or more) properties to contact.

Let a guest, g, enter the market at time, t. Each guest searches for a property to contact from a consideration set. The guest receives utility from property, h, according to a linear combination of property characteristics, a property random effect and a guest specific error term according to the equation below:

$$u_{ght} = \alpha_0 + (p_{ght} + f_{ght})(\alpha_1 + Z_g'\alpha_2) + f(X_{ht}, Z_g)'\beta_1 + \kappa_N + \gamma_h + \epsilon_{ght} \tag{3}$$

where X_{ht} is a vector of property characteristics including review quality, property type and whether the host is a property manager. Z_g is a vector of trip and guest characteristics (Nights, Age, Guests), $f(X_{ht}, Z_g)$ is a set of interactions between guest and host characteristics, p_{ht} is the nightly price of the property for the trip, f_{ght} is the platform fee, κ_N is a neighborhood fixed effect and η_{ght} is an unobserved component of the utility which is distributed according to the type 1 Extreme Value (EV) distribution with variance 1. γ_h is a normally distributed listing level random effect. The random effect is included to account for unobserved heterogeneity at the listing level.

The searcher can also choose to take the outside option and leave. The searcher's value of the outside option is determined by the following equation:

$$u_{got} = T_{gt}'\mu + \kappa_t + \alpha log(H_{gt}) + \epsilon_{got} \tag{4}$$

where T_g are guest and trip characteristics, H_{gt} is the number of listings in a guest's consideration set, κ_t are month of check-in fixed effects and ϵ_{got} is a type 1 EV error term.

[11] For example, Ghose and Yang (2009) and Jeziorski and Segal (2013).

The probability of making a choice between a particular property and the outside option is determined by the relative utilities of the two options, search costs, the continuation value of searching and the probability of booking a particular inquiry. Suppose that a searcher can only send an inquiry to one listing. The probability that a searcher sends an inquiry to property, h, as opposed to choosing the outside option is determined by the following equation

$$Pr(u_{go} < b_{gh}u_{gh} + (1 - b_{gh})u_{go} - c) = Pr(u_{go} + \frac{c}{b_{gh}} < u_{gh}) \tag{5}$$

where b_{gh} is the perceived probability that searcher, g, books property h and c is the search cost. In reality, there is a continuation value of sending an inquiry that is likely to be higher than the value of the outside option because some searchers do send more than one inquiry. Let b'_{gh} be the rate with which a searcher books any listing on Airbnb and suppose that any listing which the searcher books has equivalent value to the first listing which the guest sent an inquiry to. The searcher's decision problem is then:

$$Pr(u_{go} < b'_{gh}u_{gh} + (1 - b'_{gh})u_{go} - c) = Pr(u_{go} + \frac{c}{b'_{gh}} < u_{gh}) \tag{6}$$

In either case, the consumer surplus in the above model depends on the value of the outside option and the magnitude of the effective search cost, $\frac{c}{b_{gh}}$. The effective search cost is difficult to identify without making strong assumptions because it is not clear how searchers' expectations of booking probabilities are formed. The reason is that searchers on Airbnb typically do not have any experience with using the site and rejection rates are not publicly disclosed.[12] The above two assumptions about b_{gh} have a small effect on the quantitative results because the calibrated search cost parameter is small.

The estimation procedure requires assumptions about the empirical analogue to the consideration set of each searcher. Consider the case when a searcher sees a set of listings in the first browsing session and immediately sends an inquiry. The consideration set for that scenario is composed of all the listings seen in that browsing session. In other cases a guest sends an inquiry after many days of search for a particular trip. Some properties that the guest browsed could have been booked by someone else before the decision to send an inquiry was made. Lastly, guests sometimes send an inquiry to a host without seeing a property in the search results. This might occur if the guest navigated to the property through an outside link.

I include a property in the consideration set if the guest saw the property and sent an inquiry to any property up to 2 days afterward. If a guest did not send an inquiry, then I include a property in the consideration set only if it was seen on the last 2 days

[12] In some other matching markets, such as college admissions, there is public information on admissions rates and searchers may behave differently.

of search. Guests who sent an inquiry more than a day after the last search, who sent an inquiry to a property that was not observed in search or who viewed fewer than 10 total listings are excluded. I make the above assumptions so that the estimation data contains only decisions that mirror the underlying model of behavior. The variation in consideration sets provides an important form of identification for the model. Due to complicated supply and demand dynamics, the amount and quality of listings available in the market varies both by the week of the trip and the week of the search. Therefore, searchers who enter the market at a given time before a trip might see very different listings depending on the week of the trip. This variation allows me to identify how the value of the outside option for searchers varies both by the week of the trip and the time in advance of the trip that the search occurred.

No matter how many covariates are added to the model, there will still be important aspects of the property characteristics that are difficult to observe by the econometrician but not by the guest. For example, the property may have stylish furniture in the picture. Such a listing is likely to charge a higher price than an otherwise similar property with worse furniture. I use a control function approach to address the endogeneity of price and omitted variable bias (Smith and Blundell (1986) and Petrin and Train (2010)).

I use the suggested price for the property by Airbnb as an instrument for price. Starting in late 2012, Airbnb began displaying a suggested price to some properties. The suggested price is calculated by taking a weighted average of the recent transaction prices of similar properties based on geography, reviews and several other characteristics. The similarity of listings is based on an arbitrary subset of characteristics chosen by a software engineer at Airbnb. If the true price is predicted using a full set of characteristics and a suggested price term, then the effect of the suggested price should only be due to the fact that it was seen by the host and served as an anchor. Therefore, conditional on controls, the suggested price should be exogenous. I combine the instrument with the estimation using a control function approach. In the first stage, I regress the listed price on the instrument and controls. The error term is then added into the utility specification in the second stage. I use a control function procedure because the non-linearity of the choice probabilities makes simpler procedures like two stage least squares unsuitable for this application.[13]

The first stage equation is:

$$lp_{ht} = X'_{ht}\beta + S_h\kappa_1 + IS_h\kappa_2 + \nu_{gpt} \tag{7}$$

where lp_{ht} is the listed price of a property at time t, X_{ht} are property characteristics, S_h is the suggested price in March 2013, and IS_h is an indicator that takes the value of

[13]The standard errors are currently computed without taking into account the estimation error in the first stage. I plan to recompute them using the bootstrap.

1 when there is no suggested price. Not all properties have a suggested price because the suggested price algorithm requires there to be enough similar historical transactions to the property. The suggested price was updated over time but those updates were not recorded consistently. Therefore, I use the suggested price at the beginning of the estimation sample. If the algorithm does not change much over time and if the suggested price influences price setting then the instrument should still be valid.

The residuals from equation (7) are added to the estimation procedure so that the utility specification is as follows:

$$u_{ght} = \alpha_0 + (p_{ght} + f_{ght})(\alpha_1 + Z_g'\alpha_2) + \hat{\nu}_{ht}\eta_1 + IS_h\eta_2 + f(X_{ht}, Z_g)'\beta_1 + \gamma_h + \epsilon_{gh} \qquad (8)$$

The control function residual can be interpreted as an estimate of the omitted variables in the demand equation that are correlated to price. If $\hat{\nu}_{ht}$ is greater than 0, the listed price of a property is higher than the predicted price conditional on property characteristics and the suggested price. One interpretation if this residual is that good unobserved characteristics allow hosts to charge higher prices.

Another complication with the above specification is that random utility models overstate the benefits to variety because the characteristic space expands with every product. In practice, products crowd each other out to some extent in the characteristic space. I follow Ackerberg and Rysman (2005) in adding a term for the log of the size of the consideration set to the value of the outside option in the estimation. This term corrects for the tendency of the utility from a random utility choice to diverge as the set of options grows. The correction suffers from bias if those individuals who view larger consideration sets conditional on observed characteristics also value the outside option differently than those who view smaller consideration sets.

3.2.1. Demand Estimation

The estimation sample consists of 6273 users with Airbnb accounts searching in City X between March 30, 2013 to June 25, 2013 for trips between April 2013 through July 2013. These users collectively viewed a total of 360 thousand listings in search. To be included in the sample, searchers had to have fewer than 9 guests, fewer than 15 nights of stay and must have searched before the day of the check-in. Searchers who only had 1 search were also excluded from the sample to reduce noise. Less than 1% of those searchers actually contact a host and these searchers are typically viewed as "non-serious" by analysts within the company. I also exclude those searchers who saw fewer than 10 or more than 500 properties because such observations are either incomplete or likely driven by bots. Lastly, I exclude views of "Shared" rooms which comprise $< 1\%$ of all inquiries. Of those searchers left, 54% chose the outside option.[14]

The estimates from the demand model without and with the correction for large consideration sets are displayed in Table 2 and Table 3. In both tables, Column 1 excludes the control function residual and Column 2 includes the control function residual. Each coefficient estimate and standard error is normalized by the coefficient on price in the estimation procedure.

Across specifications, guests value more reviews and higher rated reviews as expected. Further, trips with more guests are less price sensitive and value entire properties as opposed to private rooms. Older guests are less price sensitive, presumably because they are richer. The estimates with the control function residual tend to have lower coefficient estimates, suggesting that unobserved heterogeneity was indeed correlated with price. The specifications with the corrections for large choice sets further decrease the estimated value of listing characteristics.

The value of the outside option (inclusive of effective search costs) compared to the value of a listing is important for counterfactuals because policy changes affect the set of listings that people see. If the listings shown are better, then the searcher should be less likely to choose the outside option. The estimation results show that the outside option is less valuable for trips with more than 1 night because the fixed cost of arranging a stay on Airbnb may only be worth incurring for longer trips. The outside option is also more valuable for searches occurring further in advance of the check-in.

The standard deviation of listing random effects, which account for the listing level heterogeneity conditional on observables, ranges from 11$ to 21$ per night depending on the specification. Therefore, the variation of listing specific components of utility is about the same as the impact of having good reviews. The standard deviation of the error term ranges between $40 and $46 per night. The unexplained component of utility is important because it often takes on values that are much larger than the values of observable listing characteristics. The error term is driven by the fact that characteristics which are observable to searcher (photo quality, amenities, property size, etc...) are not included in the specification. Further, the error term can be inflated by unobserved preference heterogeneity and displayed listings on the website that are not viewed by the searcher.

3.3. Simultaneous and Sequential Search

Some searchers send multiple initial inquiries and continue search after they are rejected. The propensity of searchers to engage in intensive search is a function of their characteristics. I estimate Poisson count of models of the number of inquiries sent initially and after

[14] The actual conversion rate to sending an inquiry is lower because many searchers never create an account. I exclude non-registered searchers because I do not observe demographic information about them.

rejection (shown in Table 3). For simultaneous search, the number of inquiries initially sent by a searcher minus 1 is regressed on trip and searcher characteristics. For sequential search, the number of subsequent inquiries is regressed on trip an searcher characteristics. The Poisson regressions are biased because the potential number of inquiries a searcher is willing to send is capped by the amount of listings in the market which are better than the outside option. In the simulation, I calibrate constants which inflate the number of potential inquiries that a searcher would like to send if there are enough good properties. The search calibration accounts for the fact that some searchers are more likely to search intensively than others. For example, individuals who have successfully used the site before are more likely to continue search after an initial rejection.

4. Rejection and Screening

Hosts receiving inquiries from potential guests choose which of them to accept or reject. In the model, each host evaluates inquiries in sequence based on guest and trip characteristics.[15] If an inquiry is suitable, the host responds with a non-rejection and waits for the guest to eventually book. If the inquiry is not suitable, the host rejects and waits for the next inquiry. If the guest is not rejected and agrees to book, then the host rejects subsequent inquiries until the intial guest books.

There are three reasons why hosts reject guests in my model: congestion, "stale" vacancies and screening.[16] Congestion occurs when a guest sends an inquiry to a host who is about to transact with someone else. Transactions take time to clear because there is almost always some time between a communication and transaction on Airbnb. This gap happens because the guest takes time to return to the site after a response and enter the credit card information. Further, there are sometimes further details being discussed even after the first response by a host. I classify inquiries to hosts which are subsequently booked by a previously contacting guest as congestion. Not all congested inquiries receive an immediate rejection. Instead, the host may tell the guest to wait until there is a response from the previous inquiry. Congestion occurs for 5.6% of inquiries in the US for 2012.

A second type of rejection occurs because hosts are not available to anyone for a set of dates. There are two ways in which stale listings manifest themselves in the data. First, hosts can update their calendars to state that they are unavailable for a

[15] In practice, there are some cases when a host receives inquiries in parallel. For example, a host might receive several inquiries at a time if he checks Airbnb infrequently. I abstract from this scenario because many hosts are notified by text or email of an inquiry and have an incentive to respond quickly. In other search markets, such as college admissions, a parallel model of decision making by the seller is more appropriate.

[16] Appendix C contains a static urn and ball model which demonstrates how rejections arise according to congestion, stale vacancies and screening.

set of dates. For 56% of host-weeks in the sample, hosts update their calendars to be unavailable and are not booked by anyone for that week. For these stale vacancies to matter, hosts must update at a point when searchers are active in the market. In fact, many properties update their calendar more than 2 months ahead of the check-in date, so that few searchers have time to see the stale vacancies. In the data, 21% of all inquiries are sent to listings that are later updated to be unavailable for at least one of the dates of an inquiry and are not booked for any of the other dates of inquiry.

Some hosts with stale vacancies never update their calendar. This happens because updating the calendar is costly, because the host wants to learn information about demand or because the host forgets. These types of stale vacancies result in observations in which a host rejects all inquiries for a particular set of dates. Figure 6 shows the distribution of rejection rates (excluding congested inquiries and those for which a host updated her calendar) by hosts in a given week of check-in if the host received at least 5 inquiries for that week. There is a wide dispersion of rejection rates and a noticeable excess mass at 1, with over 10% of host-week combinations rejecting all inquiries. However, nothing in the data distinguishes whether any particular host rejected all inquiries due to actual unavailability or due to high selectivity. If hosts reject each inquiry at a rate of 50%, then there should be fewer than 3% of host-week combinations that reject all inquiries. At least some of the cases in which a host rejects everyone are probably due to stale vacancies. The upper bound for inquiries rejected due to unavailability includes all inquiries to hosts who reject all inquiries for a particular week. The lower bound is the set of all inquiries to hosts who eventually update their calendar to be unavailable. In total, the upper bound on inquiries rejected due to stale vacancies is 32% and the lower bound is 21%.[17]

The last type of rejection occurs because hosts are screening amongst potential guests. Screening is determined by the characteristics of interacting searchers and hosts. Figure 7 displays a histogram of the mean rejection rates (excluding congested inquiries) by property for all of 2012, conditional on a property receiving at least 10 inquiries. I exclude congested inquiries and inquiries to hosts who eventually updated their calendar to be unavailable. Many properties reject all or almost all inquiries while others accept almost everyone. The heterogeneity occurs because some properties are either more selective, more in demand, receive different types of inquiries or are more likely to not updated their calendar than others. Many of the listings that rejected close to 100% of inquiries rarely even responded and were eventually removed from the website. The remaining inquiries are rejected either due to screening or due to hosts who do not update their calendar. An upper bound on screening rejections includes those cases in which hosts rejected all inquiries in for a given week of trip while the lower bound does not. The upper

[17] I've also estimated an explicit model that allows me to identify the share of inquiries rejected by screening versus stale vacancies. That model determines that 5.1% of inquiries are affected by stale vacancies for which hosts never updated their calendar.

bound on immediate rejections due to screening as a share of all inquires 31% while the lower bound is 20% in 2012.

Stale listings and screening account for most of the rejections that occur on Airbnb. These two frictions are approximately the same magnitude and their importance depends on assumptions. On the other hand, congestion, which has been a key focus in many theoretical models of directed search, is a lot less important. In total, 59% of inquiries are affected by frictions either through screening rejection, congestion or a stale vacancy. If search costs are large, then these results already suggest that there are large welfare costs of search frictions.

There are some ambiguities in the classification. Listings that update their calendar to be unavailable might have been booked had a good enough offer came along early enough. Alternatively, they may have been booked off of the Airbnb platform.[18] There is no good data on how often hosts multi-home in several accommodations marketplaces but this type of behavior may be important for the counterfactuals (i.e. Athey, Calvano and Gans (2013)). Another cause of error is that the text classification process is not fully accurate and could have mislabeled some responses. Lastly, some screening occurs later in the conversation and is not captured by my methodology.

4.1. Screening Model

Screening occurs on Airbnb because hosts have preferences over when and whom they host.[19] For example, a host can find a guest untrustworthy because the guest is not reviewed, has a vague inquiry or doesn't have enough other profile information filled in. Hosts also reject guests because the check-in dates of the inquiry can break up a bigger, uninterrupted time of availability for the host, preventing future inquiries. Lastly, hosts may be waiting for a better guest/trip combination or might consider a particular inquiry too much of a hassle.[20]

I model the probability that a seller rejects a searcher as a logistic function of guest characteristics, trip characteristics, seller characteristics and market demand. Consider

[18] In some cases, hosts indicate on their calendar that they were booked on another site. 1.81% of inquires are sent to these hosts. There is no good evidence at Airbnb on how frequently transactions initiated on Airbnb are taken off of the platform. There are large incentives for guests and hosts to keep transactions online because of the insurance, reputation and secure monetary transfer that Airbnb offers.

[19] Bargaining plays a key role in other matching models with transferable utility between the two sides of the market. Bargaining infrequently results in transactions on Airbnb because there is often no Pareto efficient exchange possible. The potential cost to a host from a non-trustworthy guest, for example, is perceived to be much greater than the potential earnings from the stay. Furthermore, hosts might consider guest who immediately ask for a discount less trustworthy.

[20] The above reasons are evident in Airbnb surveys of hosts and common responses by hosts to guest inquiries. They are corroborated by the screening model estimates.

the estimating below

$$Pr(R_{gh}) = Pr(\alpha_0 + Z_h'\delta + f(X_g, Z_h)'\beta + \gamma_h + \eta_{gh} > 0) \tag{9}$$

where η_{gh} is the logit error term, R_{gh} is an indicator for whether the response is a rejection, X_g are the number of guests, guest reviews, guest gender, weekly demand, days in advance of the trip nights, guest age and month of check-in. Z_h are property type, property manager indicator, host age, the number of reviews and price. $f(X_g, Z_h)$ are interactions between guest and listing characteristics. $\gamma_h \sim N(0, \sigma^2_{sh})$ represent listing specific random effects. The random effects account for heterogeneity in hosts' baseline propensity to reject. I account for the dynamic aspects of the host decision by controlling for the time in advance of the trip of inquiry and for the overall demand for each week of check-in. Nonetheless, the above model is incomplete because although it captures the decisions of hosts, it cannot be interpreted as a utility. In order to infer the utility of hosts, I would need to estimate a full structural model of host decision making with dynamic decisions driven by host expectations of future demand.

The potential dataset for estimation consists of all non-foreign language inquiries sent by guests in City X between January 2013 and July 2013. Each inquiry is then classified as a rejection according the procedure outlined in subsection 2.4. I exclude inquiries in which congestion occurred and in which the host updated her calendar for the inquiry dates after the inquiry to indicate unavailability. The final dataset consists of 18145 observations of which 44% were rejected. I include cases in which the host rejected all inquiries, assuming for the case of the simulation that cases when the host rejected all inquiries for a week was due to screening.[21]

Table 4, panels a - c, displays the results of specifications with and without hosting and guest specific random effects. Less "trustworthy" guests and inquiries which require more hassle such as last minute and short stays should be rejected more often. Panel (a) displays the coefficients on trip and guest characteristics of inquiries. Reviewed guests and females are less likely to be rejected, presumably because hosts find them more trustworthy. Trips for 3 - 6 nights are less likely to be rejected than trips with less than 3 nights. Inquiries which are about a month ahead of the check-in date are less likely to be rejected than inquiries further or closer to the check-in date. The effect of a guest having prior reviews stands out as being an order of magnitude larger than all the other effects. Market conditions also matter for rejection behavior. The more overall demand there is in the market for the week of check-in, the more likely a host is to reject. In the specification with random effects, the standard deviation of the propensity of hosts to reject is large compared to the coefficients. This confirms previously discussed analysis which indicated that some hosts are a lot more selective than others.

[21] I plan to experiment with alternative assumptions in an Appendix.

Panel (b) displays the coefficients on host characteristics in the regression. More expensive properties, younger hosts and entire properties are more likely to reject guests. Property managers (hosts with more than 4 active listings) are less likely to reject because they care less about interacting with guests and operate more like hotels. The interaction between certain types of hosts and certain types of guests is important because it potentially generates mismatch in equilibrium. For example, some types of guests may really like some types of hosts but the hosts could be indifferent between the two types. In that case, a decentralized matching process potentially results in a suboptimal match. Panel (c) displays the logit coefficients on interactions between guest and host characteristics. As expected, property managers are less likely to reject last minute inquiries than non-property managers. Hosts renting out entire properties are comparatively less likely to reject trips with more guests and more nights compared to hosts renting out private rooms. The above results show that there are predictable conditions under which inquiries are likely to be good matches and other conditions under which that is not the case. Furthermore, there is significant heterogeneity in both the selectivity and preferences of hosts regarding the inquiries they reject.

5. Simulation of Equilibrium Outcomes

In this section I describe how to combine the search and screening models into a model of market equilibrium. I calibrate an equilibrium model and use it to study the mechanisms underlying search frictions. The goal of the model is to generate market level matching outcomes from micro-foundations. My model has few free parameters but fits the data well.

The simulation is similar to Roth and Xing (1997), which studies congestion in the clinical psychologist market. My model builds on that paper's approach by estimating preferences from the data, by modeling multiple frictions and by comparing model outcomes to empirical moments. An alternative way to condition the model on the data would be to estimate rather than simulate all of the parameters. I chose to simulate because most of the calibrated parameters in the simulation have close empirical analogues in the data and because simulation is faster than estimation.

5.1. Simulation Setup

For a given check-in week in City X, I observe searchers and bookers on Airbnb. I also observe any listings that were visible for that week. Every searcher who enters the market looking to stay in City X for the week of the simulation draws a consideration set, receives a mean utility from every listing in the market and draws a random utility shock distributed according to the demand estimates from column (2) of Table 3. Similarly, each listing receives a mean probability and a random error term conditional on searcher and listing characteristics from the logit model of rejection in column (1) of Table 4. The same process is repeated for each subsequent searcher that enters the market.

I collapse the 7 days of the week being modeled into 1 time period to simplify the simulation. Each listing can only be booked once in each week. If a listing is booked for 3 days, I assume that the other 4 days are no longer going to be available. In the data, 22% of hosts who receive an at least one inquiry in a week book more than 1 trip in that week. I avoid modeling this behavior because the model fits the data and accounting for multiple bookings adds complexity to the model. If a guest is looking for a stay of more than 7 days, then only the 7 days are used for the calculation of surplus and revenue in this section. Otherwise trips that cross into other weeks would affect outcomes for the simulation week.

The model relies on the calibration of several parameters related to market clearing and search intensity. All of the calibrated parameters are seen in Table 4. The time to transact is determined according to an exponential distribution whose mean is the empirical mean of time to transact in the data. I assume that the time between browsing and sending an inquiry is negligible. Properties sometimes update their calendar to be unavailable for a set of dates. I calibrate the distribution of the time in advance of the check-in date for which availability is changed to an exponential distribution with an appropriate mean and the share of properties that set unavailability to the share in the data.

There are three parameters in the model that do not have direct analogues in the data: γ, μ_{sim}, and μ_{seq}. I discuss each parameter and how it is calibrated below. γ determines the correlation in the consideration sets of searchers that enter the market at the same time. This parameter, in part, determines the amount of inquiries that are rejected due to congestion. However, because I am collapsing 7 days of the week into one unit of time, my model will mechanically generate more congestion than the data. In the data, 86% on inquiries include a Friday or Saturday as part of the days of stay. I use this information and an urn and balls model of matching to adjust the the share of congested inquiries moment to be matched by 24%..

The parameters μ_{sim} and μ_{seq} determine the extent of simultaneous and sequential search. The amount of initial inquiries sent by a searcher is determined as follows. Each searcher draws a random Poisson variable, n_{sim} with mean equal to the product of the predicted mean from the Poisson regression in subsection 3.3 and a calibrated constant, $\mu_{sim} > 1$. The searcher then sends inquiries to the minimum of either $n_{sim} + 1$ or the number of viewed listings with utility greater than the outside option. Sequential search

[21]The 24% multiplier is calculated using the urn and balls model described in Appendix C. The multiplier is determined by the ratio of the expected congested inquiries in the urn and balls model with all 1197 searchers compared to the share of congested inquiries in the urn and balls model with two separate markets, one with $.86 * 1197$ searchers and one with $.14 * 1197$ searchers.

is treated in the same manner. A searcher who is rejected draws a Poisson random variable, n_{seq}, according to the expected mean from the Poisson regression multiplied by $\mu_{seq} > 1$. A draw of 0 implies that the searcher does not continue search. If the draw is greater than 0, then the searcher comes back to the market 1 day later and sees the entire choice set. The searcher then sends an inquiry to the minimum of n_{seq} and the number of properties remaining which are better than the outside option. I use a grid search over values of the three parameters, γ, μ_{sim}, and μ_{seq}, to calibrate the model. I find the set of parameters that minimize a weighted euclidean distance between outcomes of 50 simulations and the empirical moments in the data. Each moment is weighted by the standard deviation of the moment across the simulations.

Oftentimes a transaction does not occur even if there is no immediate rejection because the guest does want to book the place, the host ends up rejecting the guest later in the conversation or because the initial classification was wrong. I assume guests leave the market after an opportunity to book with a constant probability because in prior analysis I found that observed property characteristics are not predictive in determining whether a non-rejection results in a booking.

The calibrated parameters above are sufficient to simulate the choices of agents in the market using the decision probabilities estimated in subsection 3.2. However, because the demand for inquiries is not the same as the demand for stays in a room, the demand estimates cannot be directly used to make claims about consumer surplus. I bound consumer surplus in the simulation by making assumptions on search costs and searcher's expected booking probabilities.

I assume that an inquiry takes 5 minutes to compose and send. I then set the search cost to the shadow value of time for the searcher. Assume that Airbnb users earn twice as much as the median annual income for males aged 25 - 44 in the United States.[22] If searchers work 2000 hours a year then the shadow value of time will be \$3.24 per 5 minutes. I use this search cost for the rest of the simulation exercises.

I bound the consumer surplus in the simulation by using two assumptions about a searcher's expectation for the probability of booking. In specification 1, I assume that the searcher's expected booking probability is the probability of booking only that listing. Such a specification assumes that the continuation value of searching is equal to the value of the outside option. Alternatively, I set the searcher's expected booking probability equal to the observed probability of booking any listing. Under the above assumption, the utility of booking a listing that is not the first inquiry is equal to the value of booking the first contacted listing. In practice, the results with either adjustment do not make a large difference in the consumer surplus calculation because the search costs are low relative to the benefit of booking a room. I use the calculation in which

[22] Source: U.S. Census Bureau, Current Population Survey, 2013 Annual Social and Economic Supplement.

the expected booking probability is the booking probability of only that listing the rest of the consumer surplus results.

For the week of April 10, 2013 and City X, I observe the set of all potential guests (with a user id on Airbnb) who searched for days overlapping that week. I include only searchers who enter the market within 8 weeks and before the date of the check-in date. At the beginning of time, each visible property draws a demand random effect and their availability. Each searcher, whose characteristics are taken from the data, draws a random browsing set, a number of potential simultaneous search and sends inquiry(s) according to the estimated demand model. This aspect of the simulation is an approximation because the utility of sending an inquiry should depend on the prior sent inquiries and policy by the platform which affects booking probability. The accuracy of the approximation depends on the extent to which the decision of a guest to send inquiries is driven by the utility of booking a listing as opposed to the expected probability of booking. The host who receives the inquiry rejects the guest if that host is unavailable, has already been contacted by an eventual booking or draws a random term that leads her to reject. A guest who is not rejected draws a random term that determines if that guest books. If the guest who is rejected and continues search comes back 1 day later and sends the minimum of the randomly drawn inquiries and the number of listings in her consideration set whose utility is greater than the outside option. Afterwards, the next searcher enters the market.

5.2. Baseline Results

The final choice situation includes 1197 searchers and 914 visible listings (56 days in advance of the check-in dates). Table 5 column (1) displays the outcomes that occurred in the data for the choice situation. 50% of searchers sent an inquiry and 33% eventually booked a room. In comparison, column 2 displays the results of the simulation. The model outcomes match the data well considering that most of the moments in the table were not explicitly targeted by the calibration. The most significant differences between the data and simulation is that simulation overstates the share of searchers sending an inquiry by 3% and understates the booking probability by 4%.[23]

5.3. Which Frictions Matter?

There are three mechanisms (excluding incurred search costs) by which actual market outcomes differ from the solution to the social planner's problem: rejection, limited choice sets and dynamic mis-allocation. Table 6 displays moments for cases in which

[23] The share of searchers that books is understated because, in the data, some listings can actually be booked two or more times in a given week. For example, there can be one two night stay and another three night stay for a given listing. I do not model this aspect of the market.

each mechanism is removed.[24] First consider column (2), in which all listings that would reject each searcher are removed from that searcher's choice set. Compared to the baseline simulation, removing rejecting hosts decreases inquiries by searchers because on average, worse quality listings are shown. However, the inquiries that are sent are much more effective. Without rejections, the share of searchers booking increases by 10%, the average revenue increases by \$34 per searcher and the average consumer surplus increases by \$8 per searcher. This is a large and surprising impact given the limited supply available on the platform. The improvement in matching indicates that there are suitable substitutes for rejecting properties on the platform, but that those properties are not being contacted at a high enough rate.

In Table 7, I display the equilibrium effect of each rejection cause separately. Of all rejection frictions, screening has the largest effect on booking and consumer surplus. The effect of screening in equilibrium is larger than it's frequency in the data because screening properties are more likely to be included in searchers' consideration sets and are more desirable for searchers. Further, listings that screened a particular guest might have accepted another one whereas stale listings and congested listings could not have matched with another searcher. The importance of screening suggests that Airbnb should guide guests towards hosts that are willing to transact. Secondly, Airbnb should elicit host preferences about guests ahead of time to improve Airbnb's ability to guide the guest.

Column (3) of Table 6 displays the simulated matching outcomes if searchers freely considered all listed properties rather than just a limited consideration set. The share of searchers who send an inquiry increases by 31%, the share that book increases by 12% and the revenue per searcher increases by 46\$. The effect on limited consideration sets is bigger than the cumulative effect of all rejection reasons because there are large product specific error terms. The demand estimates used in the simulation include an Ackerberg-Rysman correction. However, that correction itself may be biased because those searchers who view a lot of listings may have a higher utility from using Airbnb. Alternatively, searchers may select onto consideration sets based on unobservable components of their utility. In that case, estimates of the standard deviation of the error term and utility from listings outside of the consideration may be overstated. Appendix D includes robustness checks which show that the effect of limited consideration sets is sensitive to the standard deviation of the error term. Column (4) displays the results of the simulation if the rejection friction and the partially observed choice sets were removed together. There is a \$72 surplus gain from having both frictions eliminated at once, which is approximately equal to the sum of the gains from removing rejections and partial consideration sets

[24] In the counterfactual exercises, the searcher's expected probability of transacting given an inquiry should change. However, in the results below they do not. I will implement the correction in the future but doubt that such a correction would make much of a difference. Even if the expected booking probability per inquiry increases to 50%, the added benefit would be less than 10\$

separately.

Lastly, I consider the solution to the social planner's problem in this marketplace. The social planner dispatches each searcher to an appropriate outcome using information on random utility draws and the timing of entry and exit for every searcher and host. The consumer surplus maximizing allocation of the 1197 searchers to the 914 properties is a solution of the assignment problem with constraints. For each assignment of a searcher to a listing, the searcher must prefer the listing to the outside option and the listing must accept the searcher. Each listing can only be assigned to one searcher and each searcher can only be assigned to one listing. As in the simulation, there is a mass of unavailable listings that are not matched and a share of searchers who do not book even if they are matched. Further, I assume that the viewed number of listings in the Ackerberg-Rysman correction is equivalent to 195, the average number of considered listings in the scenario with no rejections and full choice sets. Column (5) displays the results of that counterfactual. In the optimal scenario, the booking rate by guests increases by 21%, the consumer surplus per browser increases by \$87 and the total revenue by the hosts increase by 72\$ compared to the baseline. There are two reasons why the optimal allocation differs from the one in which searchers see all options except for those that would reject them. First, fewer search costs need to be incurred for matches to occur. Second, there is a dynamic mis-allocation of listings to guests. Searchers entering the market earlier sometimes book a listing that would have provided more utility to a later entrant. Mis-allocation is an important matching friction in other empirical search models such as Gavazza (2012), which models the secondary market for airplanes.

The overall booking rate in the surplus maximizing outcome is approximately the same as the outcome in which there are no rejections and full consideration sets. At most 48% of the searchers in this market can be successfully matched in equilibrium because supply constraints limit the ability of policy to improve outcomes in the marketplace.

5.4. Platform Policy

I have shown that search frictions significantly affect consumer surplus and revenue on Airbnb. Because even small changes in conversion rates can improve profit margins, the platform should actively be aiming to reduce frictions. Below, I analyze several types of policies the platform can undertake to improve outcomes.

5.4.1. Ranking Algorithms

The order in which items are shown is a key policy for both online and offline marketplaces. For example, supermarkets strategically choose where to display various items and e-commerce sites refine their algorithms to display more relevant products. Furthermore, ranking algorithms are a major area of research within technology companies and in computer science departments. Much of the research on search and recommendation engines focuses on search for content or non-capacity constrained goods (i.e. Amazon Books). However, when the supply of a given good is capped, one buyer of a good prevents other searchers from buying that good. The preferences of searchers entering the market over time and the consideration sets they draw determine whether the good is allocated in an optimal manner.

In this section I consider two plausible ranking algorithms. The goal of the algorithms is to show more relevant listings to searchers in their consideration sets. I simulate better algorithms by deriving a counterfactual listing specific weight, w_h, and using the procedure in subsection 3.1 to transform it into a sampling weight. In the first counter-factual algorithm, the weights are calculated by averaging the non-idiosyncratic component of utility from each property amongst all searchers. The second algorithm personalizes search results based on searcher and listing characteristics. I compute the non-random component of utility for each searcher-listing pair and let that be the sampling weight in the model of consideration set formation. I also increase γ, the parameter which determines the correlation in browsing sets, to 1.5 because if searcher receive more relevant results they should be more likely to use the default algorithm rather than custom filters and browsing decisions. Table 8 columns (2) and (3) show the results of these policies in order.

The non-personalized search algorithm increases contact rates by 6% and booking rates by over 2% compared to the baseline and the personalized search algorithm increases the share of searchers contacting by 7% and the booking rates by over 2%. Both algorithms increase consumer surplus but, as expected, the personalized algorithm results in a larger surplus gain than the non-personalized algorithm. Even though personalization is better, the gains to personalization are not large. Both ranking algorithms provide small improvements compared to the full information benchmark because the random utility term matters for agent decisions but cannot be known by the algorithm creator. Furthermore, because algorithms do not fully determine consideration set formation, some searchers may miss out on good listings even with better algorithms. Lastly, the scarcity of listings in the market allows earlier market entrants to benefit more from search algorithms than later entrants, who have fewer suitable listings to choose from compared to the baseline scenario.

The demand models I use to generate the ranking algorithms do not explain a large share of searcher choice. In practice, market designers can choose how much employee time and resources to devote to generating features from data and better prediction algorithms that use those features. The increase in bookings in the counterfactual where searchers see the full choice set suggests that there are high returns to devoting resources to building better demand models.

5.4.2. Encouraging Search

Airbnb encourages more simultaneous search by giving searchers the ability to reuse their old message.[25] Column 5 of Table 8 displays the results of a policy that would double the simultaneous search propensity coefficient. Unsurprisingly, the amount of simultaneous search increases from 1.43 to 1.61 inquiries per searcher. The increase in the volume of simultaneous search is less than twofold because the consideration sets of searchers do not change. The resulting increase in the propensity to search leads to fewer than 1% more bookings. However, the increase in incurred search costs is large enough to offset the consumer surplus benefit. Therefore, policy that encourages more inquiries without encouraging more browsing will not be effective.

5.4.3. Policy to Reduce Rejections

Rejection frictions significantly decrease the matching rate and the surplus from Airbnb. The most direct way that Airbnb tries to reduce rejections is by encouraging searchers to verify their online and offline identities. Presumably, verified searchers are considered more trustworthy by hosts and are less likely to be rejected. Airbnb also has several mechanisms for detecting unresponsive hosts and removing the from search.

In this section I consider two additional policies aimed at reducing rejection frictions. The first policy removes listings that will reject a searcher with high probability (more than 60%) from a searcher's consideration set.[26] Table 8 column (3) shows the effects of such a policy. Compared to the baseline, the contact rate decreases but the booking rate does not change. Although search costs are reduced, the average quality of matches decreases as well because selective listings tend to be more desirable to searchers. Therefore, removing those listings from the choice sets of searchers reduces consumer surplus conditional on a transaction.

Another counterfactual policy is intended to reduce congestion. Under the policy, hosts are removed from search results for 24 hours after being contacted. Such a policy can reduce congestion because transactions will have time to clear without additional inquiries. Table 8 column (6) displays the results of this simulation and shows that there is a decrease in inquiries and a slight increase in booking due to this policy. Although the policy reduces rejections from congestion by 2%, as intended, there is a negligible effect on market outcomes.

[25]The platform clearly displays the following text underneath all inquiries: "Contacting several places considerably improves your odds of a booking."

[26]If this procedure leaves no viable options, then searchers are allowed to see listings whose probability of rejecting the searcher is less than .85%.

5.5. Aggregate Matching Functions, Market Tightness and Policy

The setting of the prior simulations is one market and one week. However, market conditions vary on Airbnb both across markets and over time. In this section, I vary the ratio of searchers to hosts and the overall amount of agents in the market to study how market conditions affect matching and policy. Varying market conditions allows me to estimate an aggregate matching function and to test for increasing returns to scale. This paper is one of the first to document that increasing returns to matching are quantitatively important in marketplaces.

I generate data to estimate a matching function by randomly subsampling or re-sampling agents in the market and simulating outcomes.[27] Each market condition is simulated 10 times, with the amount of listings and guests varying between 50% and 150% of the amount seen in the data. I use the simulated data to estimate a Cobb-Douglass matching function of the form:

$$\log(M_s) = \log(A) + \alpha \log(G_s) + \beta \log(H_s) + \epsilon_s \tag{10}$$

where M is the number of matches, G is the number of searchers and H is the number of listings in the market. Table 9 displays the estimated results of this equation, where the coefficients are allowed to vary by the search algorithm used.

There are two forces that can cause matching on Airbnb to either exhibit increasing or decreasing returns to scale. Firstly, a market with more options should generate better matches on average because searchers can draw larger consideration sets and because those consideration sets will include better options on average. On the other hand, if consideration sets are highly correlated then thicker markets may exhibit higher levels of congestion. The returns to scale in the the matching function, $\alpha + \beta$, equals 1.057. I reject the null hypothesis of constant returns to scale at a 1% confidence level. Increasing returns to scale also happen when I simulate a better search algorithm even though congestion increases with market thickness in that case.

Simulated changes to Airbnb policies alter the shape of the estimated matching function. The interacted coefficients in Table 9 correspond to the matching function estimates when search rank is personalized according to the procedure described in subsubsection 5.4.1. The improved search algorithm increases the share of matches due to the supply side in the market and decreases the share due to the demand side. The change in the shape of the matching function occurs because searchers are shown better options and are more likely to send inquiries. On the other side of the market, the same share of hosts remains. Therefore, searchers entering the market later are more likely to find no suitable hosts. Further, the increase in overall match rates from the policy man-

[27] I break ties in the timing of entry of searchers by adding a random exponential noise component with a mean of an hour to each realized entry time.

ifests itself in the matching function as a higher sum of α and β coefficents rather than through A, a parameter commonly referred to as the "search technology". The above exercise demonstrates why the Cobb-Douglass matching function parameters cannot be interpreted as structural.

The effectiveness of a better search algorithm depends on the extent to which the market is supply constrained. If there is a lack of options in the market then the search algorithm is not important because any additional bookings come at the expense of later bookings by searchers. If there are many options then the consideration sets of searchers are more likely to include relevant listings and there are enough listings for all searchers to book. Figure 8 shows how booking rates, revenue and consumer surplus vary as the amount of listings in the market change, holding the number of searchers constant. The difference in matches, revenue and surplus between the baseline and the policy simulation increases with the tightness in the market.

This sections support the view that online marketplaces do grow more efficient at matching as they grow. Furthermore, because good policy is complimentary to returns to scale, marketplaces with better matching policies should grow quicker. However, some aspects of agent behavior can change with market tightness and market size but are not in my model. Searchers might form bigger consideration sets if the are more listings to match with, which would result in even greater returns to scale if congestion remains a small issue. On the other side of the market, hosts may change pricing and rejection strategies with market conditions although the impact of these adjustments on matching is unclear a priori. Lastly, the matching function estimates exclude the accumulation of reputation capital on Airbnb as agents interact. Reputation capital might actually be the biggest cause of returns to scale in marketplaces (i.e. Pallais (2013)).

5.6. Experimentation

Internet companies typically run user level experiments to learn about the effects of policies. For example, a company may test a new feature by allowing 50% of users to see it and comparing average outcomes between the treatment and control group. In many circumstances such tests yield the exact information the company desires. However, in the case of experiments where there are externalities, the treatment effect estimated from an experiment is misleading. The group receiving the treatment may impose negative (or positive) externalities on the control group.[28]

Searchers who randomly see better search results have a higher probability of booking compared to the control. The control will then have a lower chance of booking because the treatment has occupied more of the good listings. I investigate whether such an effect

[28]For a similar effect in the labor market see Crépon et al. (2013) on the difference between the partial and general equilibrium effects of a job counceling program in France.

is quantitatively important by simulating an experiment in which 50% of searchers are assigned to the best overall ranking discussed in the previous sections while the other 50% receive the control. Column 1 of Table 10 displays the treatment effect of the new ranking estimated from the A/B test while column 2 displays the market level effect if every searcher saw the new ranking. The experiment overstates the true effect of the new search ranking by 1.7%, the surplus per searcher by \$4.9 per searcher and the revenue per searcher by \$3.9. The discrepancy in effects arises because the treatment group in the experiment is taking away high value bookings from the control group. Furthermore, the effect of the experiment and the market level effect do not always have to go in the same direction. Mistaken inference about experiments is a major cost for the marketplace because experimental results drive future policies and resource allocation by the company.

One way to obtain a market level treatment effect of a policy is to run a market by market experiment. However, market level experiments might not be feasible when market definitions are ambiguous, when there are few markets or when markets are not comparable. Another option for measuring the equilibrium treatment effect is to combine models like the one in this paper with experimental results. A model of market equilibrium should have parameters that are influenced by an experiment. For example, I used a particular set of sampling weights in the simulation of a better search algorithm. With experimental variation, I could estimate how an alternate ranking algorithm changes consideration set formation. The alternate consideration set model can then be used to simulate market outcomes. Importantly, such an approach does not require an exact replication of a complicated ranking algorithm within the model. What matters for outcomes is how the algorithm influences consideration set formation or other relevant features of the model. The equilibrium effects of other types of experimental interventions which change the rules of the market can be modeled in the same way.

6. Conclusion

The rate at which heterogeneous agents successfully transact and the surplus generated by those transactions is a function of the information structure of a market. I use novel data on search and communication behavior to build a micro-founded model of matching. The underlying cause of the matching frictions in the model is that guests and hosts have heterogeneous preferences and must use communication and Airbnb's site to obtain the necessary information to transact. Airbnb provides a review system, a communication platform and many other tools to reduce the cost of searching. Even with these tools, many searches fail and frictions combine to reduce transaction probabilities by 21%.

In other contexts, the costs of search frictions will vary depending on the expectations of the searcher, the potential benefits of searching, the search algorithm, and the details of consideration set formation. On Airbnb, searchers almost always have the option of using a hotel booking site to instantly book a room. In the labor and housing markets, rejection is common to most options and the rejection friction is likely even larger than on Airbnb. In other search markets, such as the college admissions market, rejection rates are widely known by applicants and the rejection friction is less likely to be important.[29] A similar methodology to the one described in this paper can be applied to other markets in order to quantify which mechanisms are the most important in generating search frictions.

Airbnb loses profit because frictions reduce the volume and revenue of transactions. Airbnb's policy makers can use the data they observe about the history of both searcher and seller behavior to improve outcomes. In this paper, I simulate policies which use such data to improve the relevance of consideration sets and to reduce the chance that rejections occur. I find that search algorithms which show more relevant results to searchers improve transaction probabilities by 2%. Policies that hide highly selective listings don't affect aggregate transaction probabilities and actually decrease surplus because the hidden listings create more consumer surplus than non-hidden listings when booked.

I show that an all knowing social planner who directs search can generate large gains in volume, revenue and consumer surplus compared to the current state of the market. The gains to consumers are due to the social planner's knowledge of each agent's preferences, which obviates the need for search. The ongoing reduction in the costs of storing and analyzing data, commonly referred to as the "Big Data" revolution, will likely have a profound impact on platforms like Airbnb because it brings the platform's information set closer to the full information benchmark. The degree to which an online platform can improve outcomes will, in part, be determined by the share of agents' preferences that can be explained by observed characteristics.

I only model short-run responses of agents to policy changes. In the long-run, policies will alter agents' market power and perception of matching probabilities.[30] Changes in market power will cause hosts to re-optimize their pricing and rejection strategies accordingly. Guests will also change their behavior depending on the relevance of search results and the perceived rejection probabilities. Furthermore, because policy has distributional effects, agents might have an incentive to conceal their type in order to receive more favorable matches or prices. It will be interesting to see how online platforms deal with long-run market dynamics.

[29] However, even in the college admissions market, incomplete information about rejection matters. Hoxby and Avery (2012) show that some high school students do not use widely available information on college admissions and financial aid to make application decisions.

[30] Rochet and Tirole (2003) and Weyl (2010) show how pricing and other policies affect the relative gains accrued by heterogeneous agents in a marketplace.

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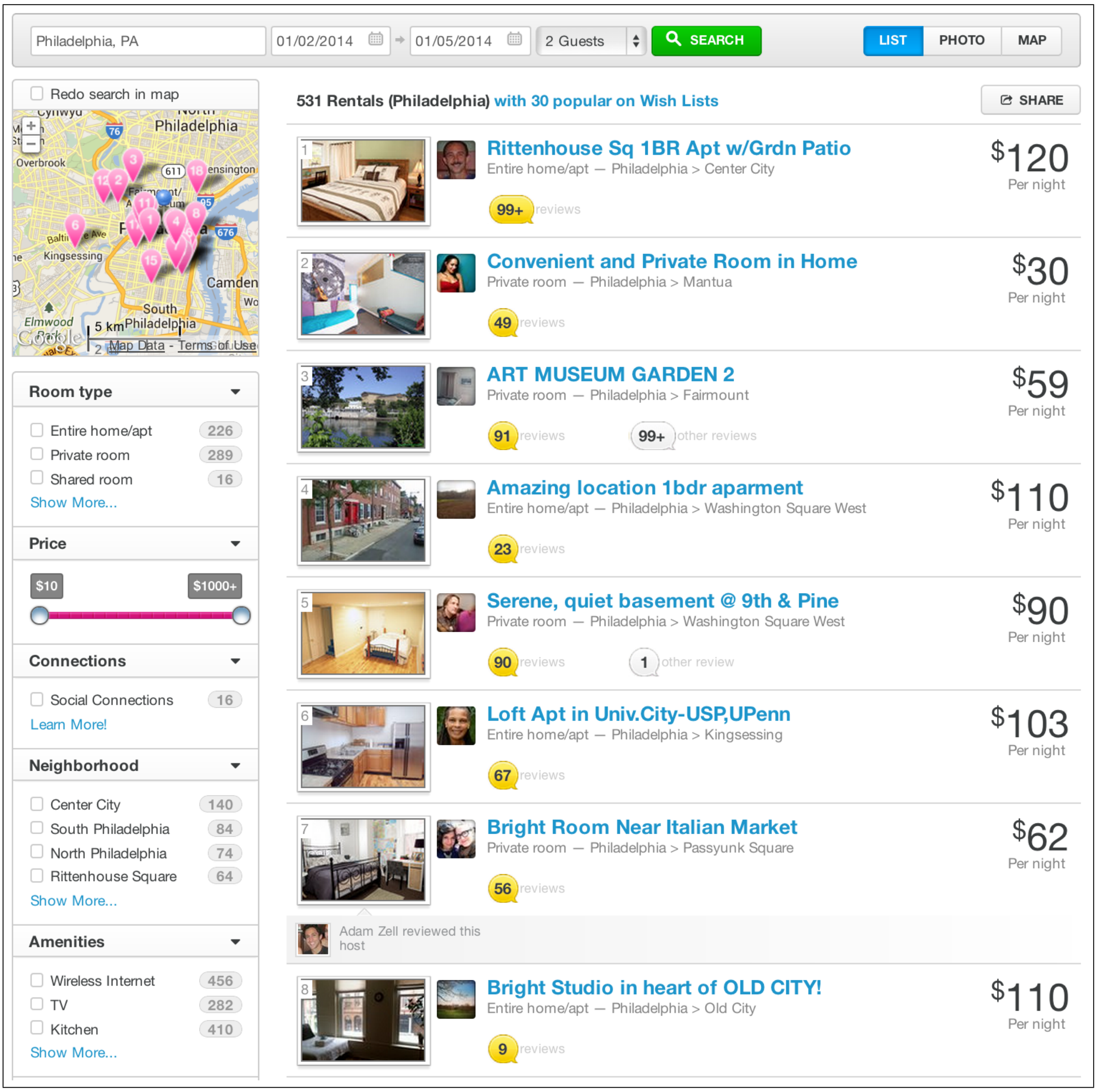
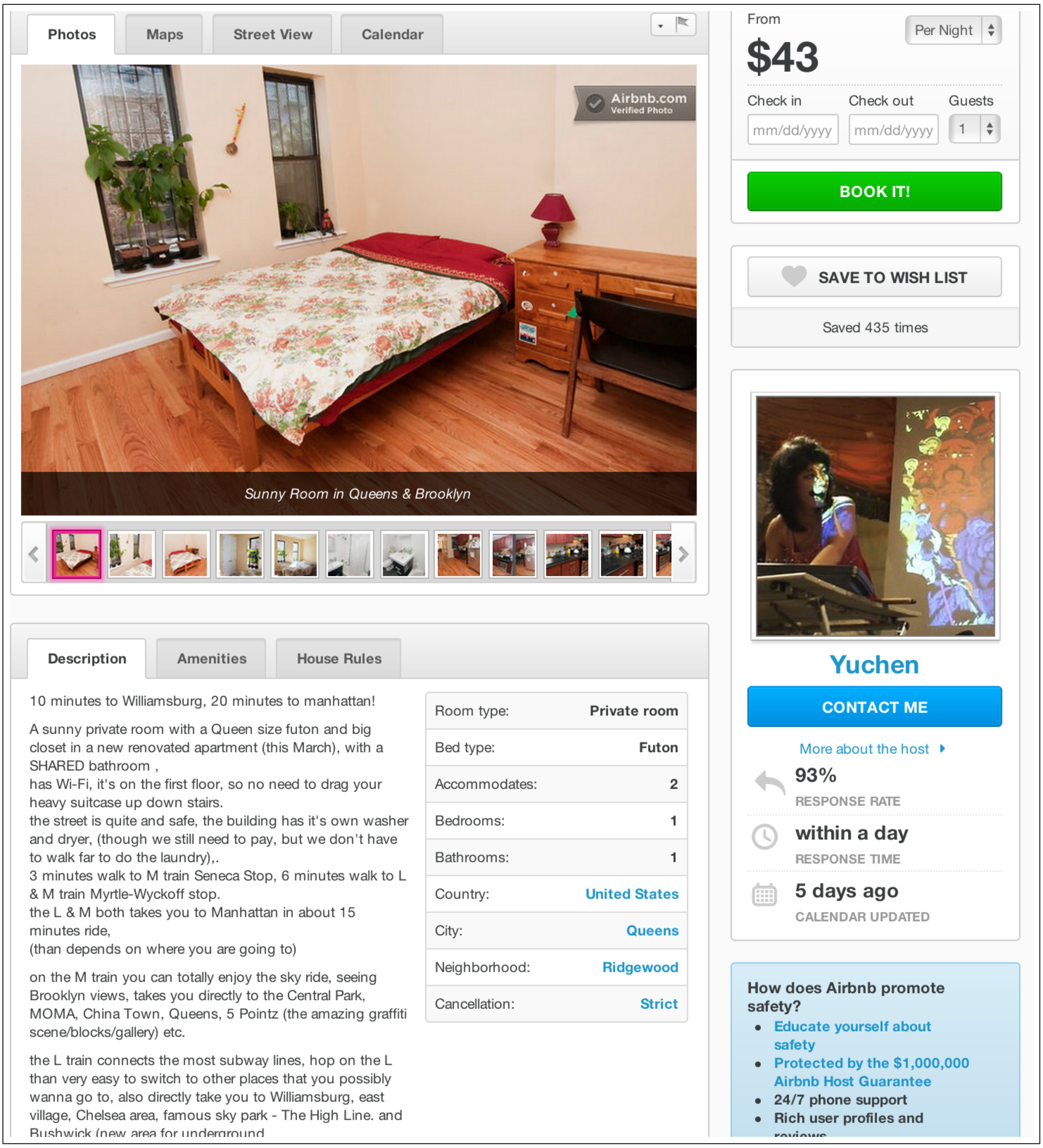
7. Figures

Figure 1: Search View



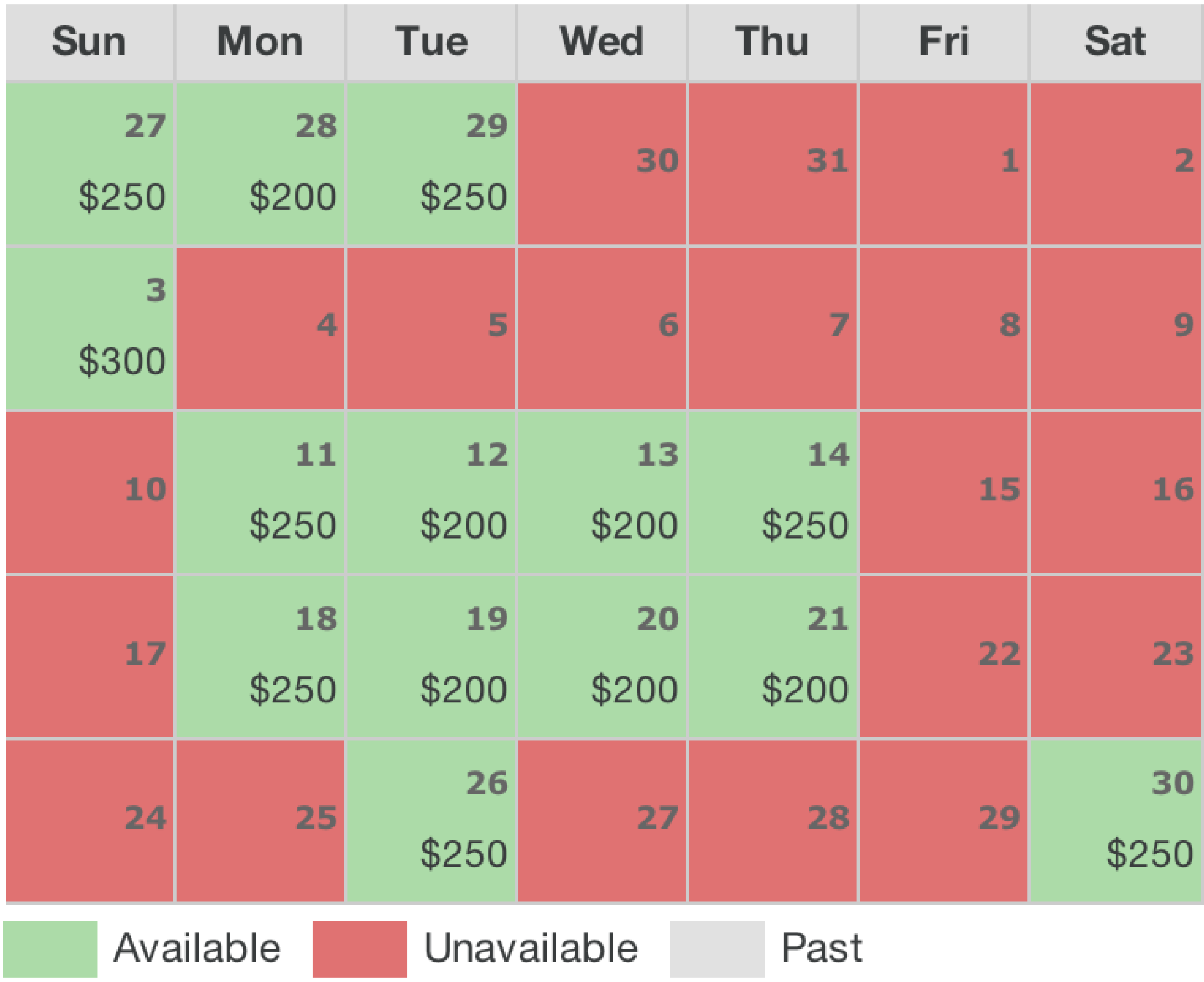
Above are the results of a search in Philadelphia for January 2, 2014 to January 5, 2014. Selecting filters or moving the map changes the set of displayed results. The searcher can scroll the page to see 21 listings before she is prompted to go to the next page of results.

Figure 2: Listing View



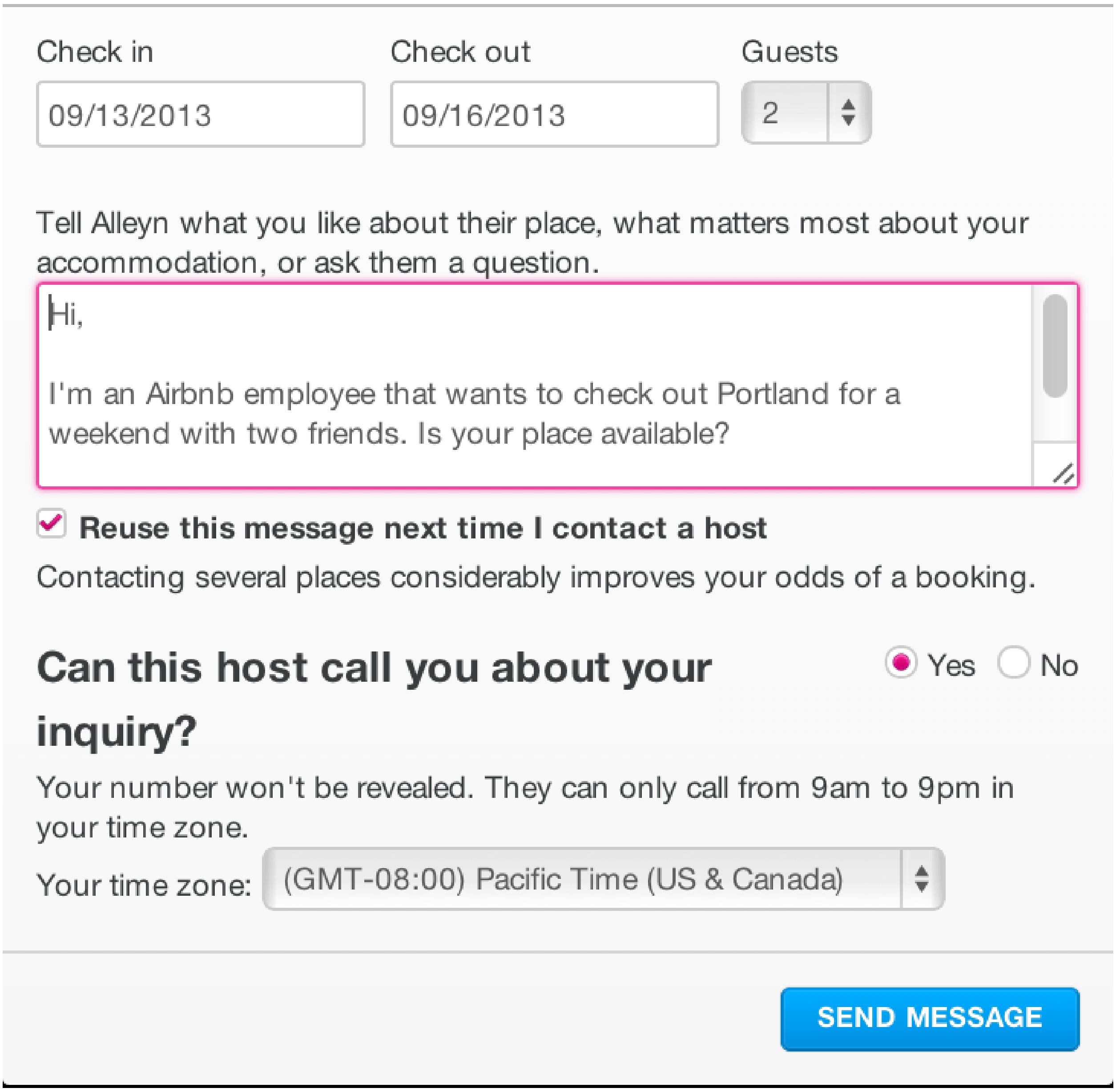
A searcher who clicks on a listing in the search results sees the following view. The ratings and text of reviews for the listing are visible lower on the page.

Figure 3: Listing Calendar



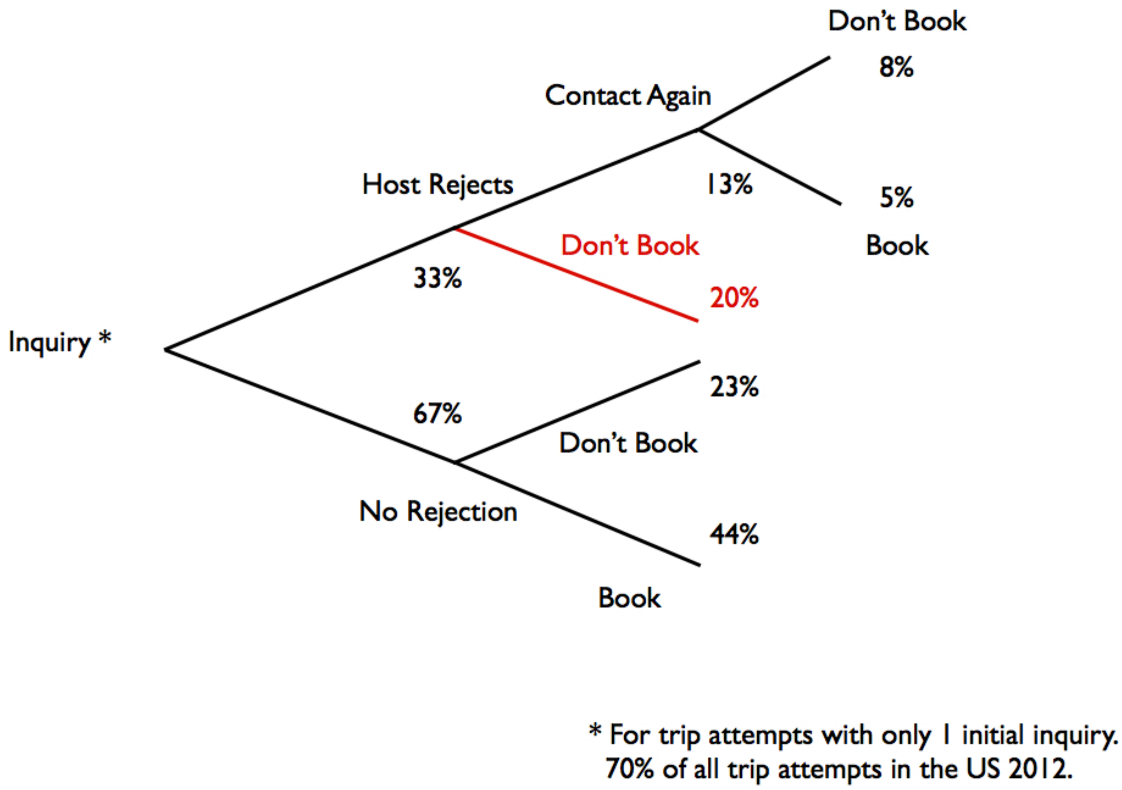
Above is the calendar tab of the listings page. Dates that have already been booked or that the host has marked unavailable are in red.

Figure 4: Inquiry Submission Form



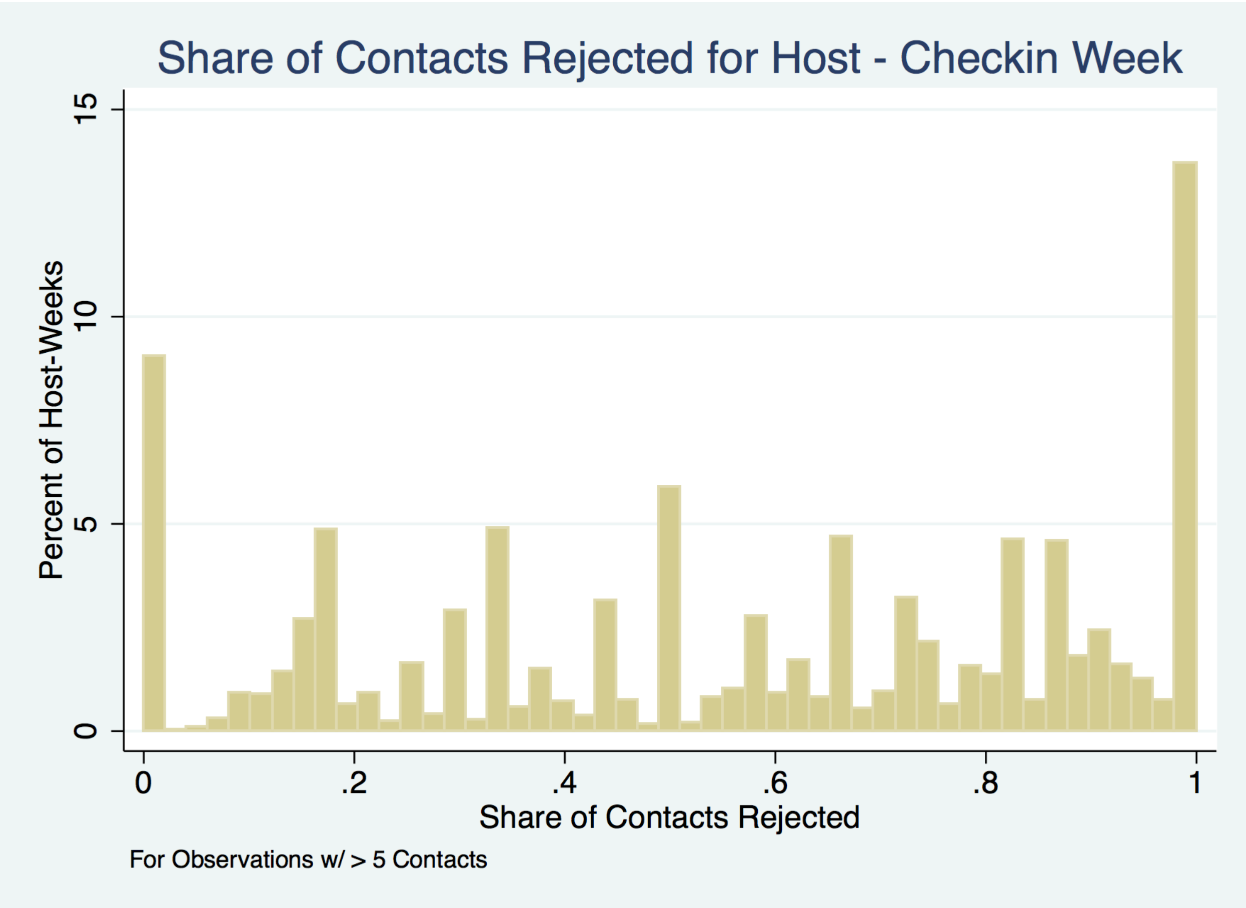
Above is the prompt that searchers see when they click the “Contact Me” button.

Figure 5: Sequential Search Outcomes



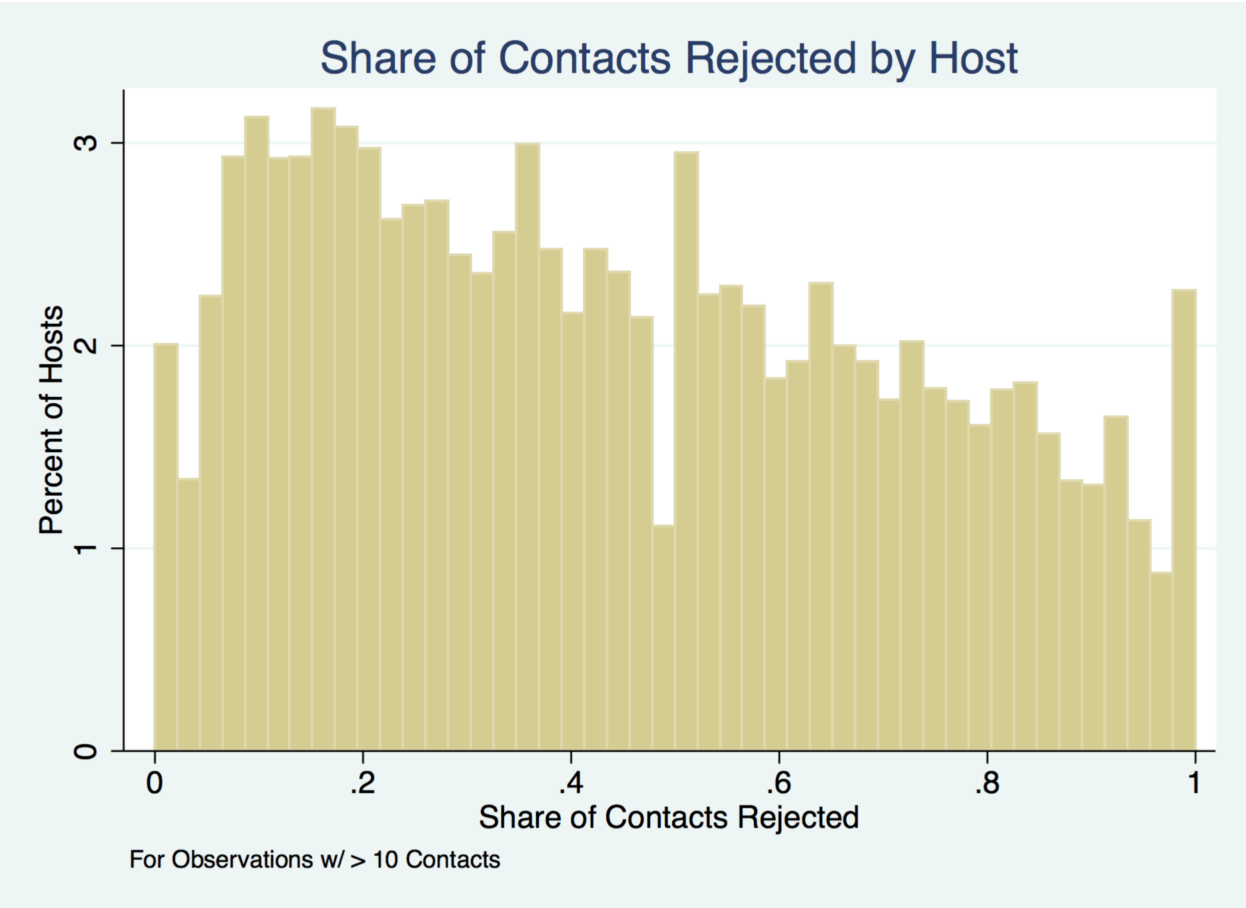
The figure displays the outcomes of searchers who send an inquiry and don't send more in the following 2 hours. "No Rejection" refers to the case when the initial inquiry was not rejected, "Book" means the guest booked at least one stay for the week and market of the initial inquiry, "Contact Again" means that the guest sent another inquiry to a listing in the same market and week as the initial inquiry.

Figure 6: Average Rejection Rates by Host-Week



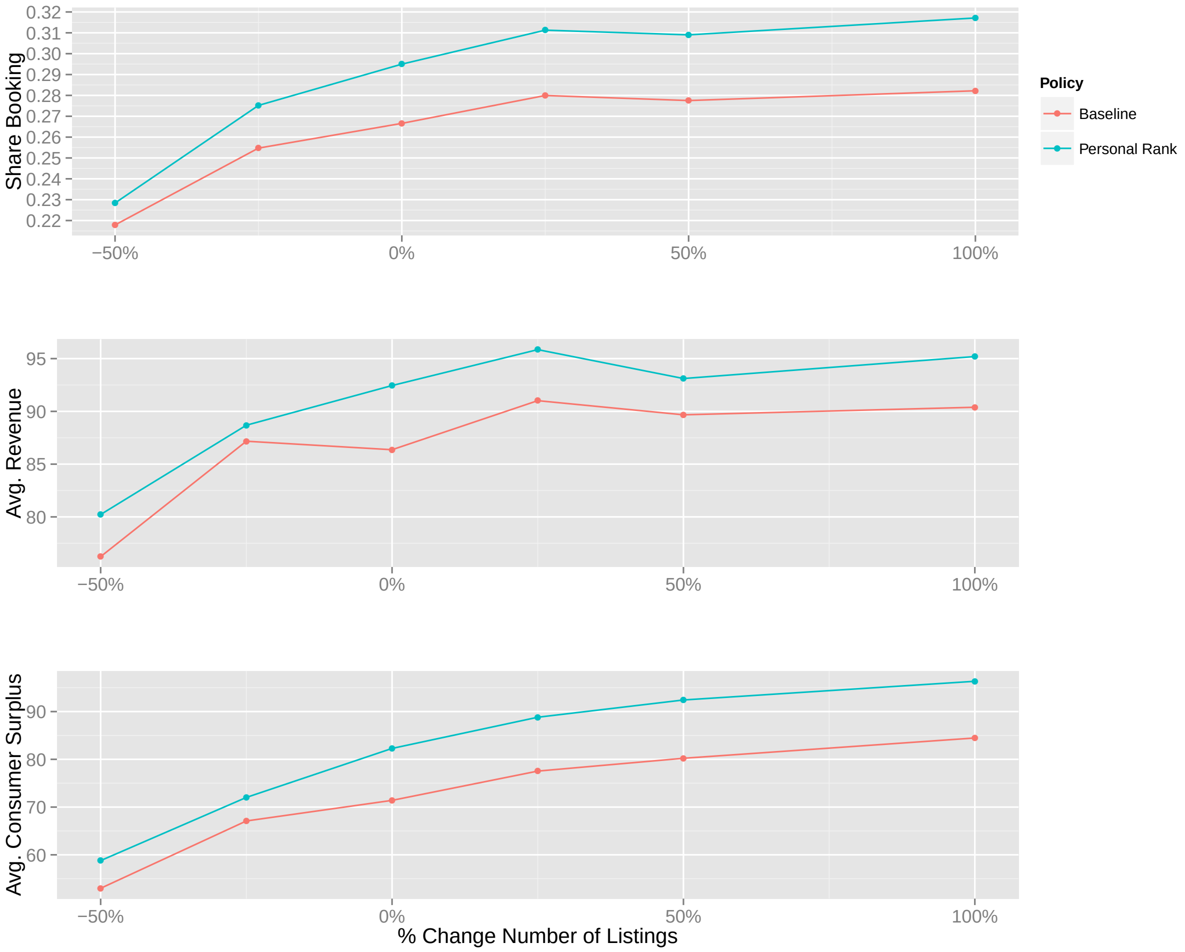
Each observation in the above histogram is a listing and a week of check-in in major US markets in 2012. Only observations with more than 5 inquiries for that week are included.

Figure 7: Average Rejection Rates by Host



Each observation in the above histogram is a listing in a major US market in 2012 with at least 10 inquiries.

Figure 8: The Effect of Tightness on Matching Rates



The figure displays what happens to match rates, revenue and surplus per searcher when the amount listings in the market changes but the amount of searchers stays the same. Each point is an average of 10 simulations given a policy and a number of listings. "Baseline" refers to the simulation that keeps current policy while "Personal Rank" refers to a search algorithm that makes searchers more likely to observe high utility listings.

8. Tables

Table 1: Does Rejection Lead to Fewer Bookings?

	(1)	(2)
Rejected	-0.503***	-0.505***
	(0.00127)	(0.00128)
Week FE	No	Yes
Market FE	No	Yes
Trip Characteristics	No	Yes
Observations	547680	547680

The above table displays the results of a linear probability model that predicts whether an individual will eventually book given that their initial inquiry was rejected. Specification 2 includes week, market and trip fixed effects.

Table 2: Demand Estimates (In Dollar Terms) With Random Effects

	Baseline	Control Function (Suggested Price)
Control Residual		0.148*** (0.037)
1 - 2 Rev. 4 Rat.	−17.820** (7.990)	−17.917** (6.987)
1 - 2 Rev. 4 + Rat.	12.024*** (3.660)	10.472*** (3.192)
3 - 9 Rev. 4.5 Rat.	7.865 (6.984)	5.487 (6.035)
3 - 9 Rev. 4.5 + Rat.	16.252*** (3.252)	12.856*** (2.817)
10 + Rev. 4 Rat.	0.332 (8.981)	−3.923 (7.768)
10 + Rev. 4.5 Rat.	12.841*** (4.272)	8.385** (3.707)
10 + Rev. 4.5 + Rat.	19.061*** (3.717)	14.117*** (3.240)
Unknown Rating	−2.865 (7.772)	−4.307 (6.723)
Prop. Mgr.	−27.875*** (3.594)	−22.935*** (3.069)
Prof. Pic.	0.956 (2.631)	1.765 (2.231)
Entire Property * 1 Guest	13.317* (7.332)	19.138*** (6.592)
Entire Property * 2 Guests	27.466*** (6.744)	31.889*** (6.091)
Entire Property * 3 Guests	14.334 (10.069)	20.391** (9.059)
Entire Property * 4 Guests	28.141*** (10.500)	32.733*** (9.466)
Entire Property * 5 - 9 Guests	66.364*** (14.942)	66.719*** (13.501)
Entire Property * 10 + Guests	0.085 (33.643)	−1.871 (30.919)
Entire Property * Price	0.149*** (0.058)	0.144*** (0.049)
Price * 2 Guests	0.061* (0.032)	0.054* (0.029)
Price * 3 Guests	0.279*** (0.048)	0.248*** (0.043)
Price * 4 Guests	0.276*** (0.049)	0.246*** (0.043)
Price * 5 - 9 Guests	0.274*** (0.060)	0.246*** (0.054)
Price * 10+ Guests	0.492*** (0.092)	0.465*** (0.088)
Price * Guest Rev.	−0.114*** (0.020)	−0.102*** (0.018)
Price * Age	0.004*** (0.001)	0.004*** (0.001)
Price * Age NA	0.178*** (0.056)	0.160*** (0.050)
Price * 3 - 6 Days Ahead	0.168*** (0.063)	0.149*** (0.056)
Price * 7 - 13 Days Ahead	0.136** (0.060)	0.121** (0.054)
Price * 14 - 20 Days Ahead	0.153** (0.062)	0.137** (0.055)
Price * 21 - 27 Days Ahead	0.159** (0.064)	0.142** (0.057)
Price * 28 - 56 Days Ahead	0.223*** (0.058)	0.200*** (0.051)
SD. Error	45.99	41.02
SD. Listing Random Effect	21.09	15.68
Num. Search Attempts	6,165	6,165

The above table displays the monetary value of characteristics (per night) associated with property listings in the demand model without random effects. The demand model is estimated on a sample of all searchers in City X from April to July of 2013. Standard errors are in parentheses. Neighborhood fixed effects are included in both specifications. "Control Residual" refers to the residual from the first stage regression of listed price on suggested price and other characteristics. "Price" refers to the per night price of the trip, "Days Ahead" refers to the number of days before the check-in at which the inquiry was sent. "Prop. Mgr." is an indicator that takes on the value 1 if a host manages more than 4 listings. "Prof. Pic." is an indicator for whether the picture was taken by a verified Airbnb photographer. "Entire Property" is an indicator variable that takes the value 1 when the entire property is being rented out.

Table 3: Demand Estimates (In Dollar Terms) With Random Effects: Correction for Large Consideration Sets

	Baseline	Control Function (Suggested Price)
Control Residual		0.140*** (0.035)
1 - 2 Rev. 4 Rat.	−17.851** (7.706)	−17.931*** (6.774)
1 - 2 Rev. 4 + Rat.	11.812*** (3.526)	10.385*** (3.090)
3 - 9 Rev. 4.5 Rat.	5.814 (6.652)	3.775 (5.776)
3 - 9 Rev. 4.5 + Rat.	14.628*** (3.077)	11.602*** (2.676)
10 + Rev. 4 Rat.	−3.945 (8.467)	−7.519 (7.362)
10 + Rev. 4.5 Rat.	8.992** (4.003)	5.199 (3.486)
10 + Rev. 4.5 + Rat.	15.542*** (3.491)	11.247*** (3.057)
Unknown Rating	−2.855 (7.383)	−4.194 (6.415)
Prop. Mgr.	−28.447*** (3.327)	−23.730*** (2.856)
Prof. Pic.	0.903 (2.435)	1.673 (2.072)
Entire Property * 1 Guest	28.371*** (1.823)	25.428*** (1.635)
Entire Property * 2 Guests	9.609 (6.941)	15.490** (6.282)
Entire Property * 3 Guests	24.347*** (6.316)	28.847*** (5.746)
Entire Property * 4 Guests	8.841 (9.634)	15.130* (8.720)
Entire Property * 5 - 9 Guests	19.425* (10.042)	24.664*** (9.103)
Entire Property * 10 + Guests	47.008*** (14.366)	49.516*** (13.042)
Entire Property * Price	−9.664 (32.990)	−9.723 (30.463)
Price * 2 Guests	0.169*** (0.054)	0.162*** (0.046)
Price * 3 Guests	0.045 (0.031)	0.040 (0.028)
Price * 4 Guests	0.240*** (0.047)	0.215*** (0.042)
Price * 5 - 9 Guests	0.230*** (0.047)	0.206*** (0.042)
Price * 10+ Guests	0.221*** (0.059)	0.199*** (0.053)
Price * Guest Rev.	0.434*** (0.093)	0.411*** (0.089)
Price * Age	−0.101*** (0.019)	−0.090*** (0.017)
Price * Age NA	0.004*** (0.001)	0.004*** (0.001)
Price * 3 - 6 Days Ahead	0.185*** (0.055)	0.167*** (0.049)
Price * 7 - 13 Days Ahead	0.167*** (0.062)	0.150*** (0.055)
Price * 14 - 20 Days Ahead	0.139** (0.060)	0.125** (0.053)
Price * 21 - 27 Days Ahead	0.155** (0.061)	0.140** (0.055)
Price * 28 - 56 Days Ahead	0.166*** (0.063)	0.149*** (0.056)
Out. Opt. * Log(Viewed Hostings)	0.234*** (0.057)	0.212*** (0.051)
SD. Error	45.43	40.79
SD. Listing Random Effect	16.65	11.66
Num. Search Attempts	6,165	6,165

The above table displays the monetary value of characteristics (per night) associated with property listings in the demand model without random effects. The demand model is estimated on a sample of all searchers in City X from April to July of 2013. Standard errors are in parentheses. Neighborhood fixed effects are included in both specifications. "Control Residual" refers to the residual from the first stage regression of listed price on suggested price and other characteristics. "Price" refers to the per night price of the trip, "Days Ahead" refers to the number of days before the check-in at which the inquiry was sent. "Prop. Mgr." is an indicator that takes on the value 1 if a host manages more than 4 listings. "Prof. Pic." is an indicator for whether the picture was taken by a verified Airbnb photographer. "Entire Property" is an indicator variable that takes the value 1 when the entire property is being rented out.

Table 4: The Determinants of Host Screening

	Baseline	Random Effects
Rev. Guest	-3.206^{***}	-3.142^{***}
	(0.109)	(0.120)
Gender Filled Female	-0.004	0.012
	(0.038)	(0.045)
Gender Filled Male	0.081^{**}	0.107^{**}
	(0.040)	(0.047)
3 - 6 Days Ahead	-0.240^{***}	-0.339^{***}
	(0.065)	(0.077)
7 - 13 Days Ahead	-0.419^{***}	-0.498^{***}
	(0.062)	(0.073)
14 - 20 Days Ahead	-0.473^{***}	-0.576^{***}
	(0.066)	(0.078)
21 - 27 Days Ahead	-0.553^{***}	-0.652^{***}
	(0.069)	(0.082)
28 - 55 Days Ahead	-0.599^{***}	-0.695^{***}
	(0.060)	(0.072)
56 + Days Ahead	-0.585^{***}	-0.623^{***}
	(0.061)	(0.075)
Guest Age < 26	0.028	0.017
	(0.047)	(0.056)
Guest Age 26 - 34	-0.036	-0.085^{*}
	(0.038)	(0.045)
Guest Age 35 - 50	-0.054	-0.102^{*}
	(0.044)	(0.052)
Guest Age 50 +	-0.020	-0.018
	(0.053)	(0.063)
N	32,293	32,293
Log Likelihood	-19,894.900	-16,755.090
SD. Host RE		1.469
Trip Characteristics	YES	YES
Month FE	YES	YES

The above table displays the coefficients on host characteristics in a logistic regression that predicts rejections by hosts. Column 1 displys results from a model without listing specific random effects and column 2 includes random effects. "Guest Rev." is an indicator variable for whether the guest has beend reviewed.

(a) Guest Characteristics

	Baseline	Random Effects
Price Listed	0.001***	0.0004
	(0.0002)	(0.0003)
Host 1 - 4 Reviews	0.106***	0.119**
	(0.034)	(0.056)
Host 5 + Reviews	−0.247***	0.229***
	(0.031)	(0.068)
Property Manager	−1.045***	−1.066***
	(0.136)	(0.180)
Host Age < 26	0.040	0.123
	(0.051)	(0.158)
Host Age 26 - 34	0.125***	0.018
	(0.030)	(0.094)
Host Age 35 - 50	−0.386***	−0.348***
	(0.036)	(0.106)
Age 50 +	−0.651***	−0.374**
	(0.062)	(0.159)
Entire Property	0.698***	0.644***
	(0.086)	(0.128)
N	32,293	32,293
Log Likelihood	-19,894.900	-16,755.090
SD. Host RE		1.469
Trip Characteristics	YES	YES
Month FE	YES	YES

The above table displays the coefficients on host characteristics in a logistic regression that predicts rejections by hosts. Column 1 displys results from a model without listing specific random effects and column 2 includes random effects. "Rev." refers to the number of reviews that the listing had at the time of the inquiry. "Prop. Mgr." is an indicator that takes on the value 1 if a host manages more than 4 listings. "Age" refers to the host's age. "Full Property" is an indicator variable that takes the value 1 when the entire property is being rented out.

(b) Host Characteristics

	Baseline	Random Effects
Prop. Mgr. * 3 - 6 Days Ahead	0.468***	0.545***
	(0.173)	(0.198)
Prop. Mgr. * 7 - 13 Days Ahead	0.531***	0.552***
	(0.168)	(0.192)
Prop. Mgr. * 14 - 20 Days Ahead	0.545***	0.666***
	(0.176)	(0.203)
Prop. Mgr. * 21 - 27 Days Ahead	0.751***	0.800***
	(0.184)	(0.215)
Prop. Mgr. * 28 - 55 Days Ahead	0.811***	0.855***
	(0.155)	(0.181)
Prop. Mgr. * 56 + Days Ahead	0.780***	0.748***
	(0.149)	(0.176)
2 Guests * Entire Prop.	0.019	−0.158**
	(0.061)	(0.074)
3 Guests * Entire Prop.	−0.200*	−0.211
	(0.112)	(0.139)
4 Guests * Entire Prop.	−0.220*	−0.190
	(0.120)	(0.155)
5 + Guests * Entire Prop.	−0.541***	−0.388**
	(0.125)	(0.170)
Entire Prop. * 2 Nights	−0.079	−0.092
	(0.095)	(0.112)
Entire Prop. * 3- 4 Nights	−0.099	−0.115
	(0.090)	(0.107)
Entire Prop. * 5 -6 Nights	−0.246**	−0.280**
	(0.106)	(0.126)
Entire Prop. * 7 + Nights	−0.518***	−0.566***
	(0.105)	(0.127)
N	32,293	32,293
Log Likelihood	-19,894.900	-16,755.090
SD. Host RE		1.469
Trip Characteristics	YES	YES
Month FE	YES	YES

The above table displays the coefficients on host characteristics in a logistic regression that predicts rejections by hosts. Column 1 displys results from a model without listing specific random effects and column 2 includes random effects."Prop. Mgr." is an indicator that takes on the value 1 if a host manages more than 4 listings. "Full Property" is an indicator variable that takes the value 1 when the entire property is being rented out. "Days Ahead" refers to the number of days before the check-in date at which the searcher entered the market.

(c) Host - Guest Characteristics

Table 3: RE Search Outcomes

	Num. Simultaneous Contacts - 1	Num Sequential Contacts
2 Initial Con.		0.226***
		(0.027)
3 Initial Con.		0.336***
		(0.040)
4 Initial Con.		0.566***
		(0.057)
5 + Initial Con.		0.933***
		(0.042)
Rev. Guest	−0.595***	0.621***
	(0.074)	(0.086)
Exp. Guest	−0.464***	−0.079
	(0.067)	(0.087)
3 - 6 Days Ahead	−0.047	0.279***
	(0.058)	(0.062)
7 - 13 Days Ahead	−0.239***	0.551***
	(0.057)	(0.058)
14 - 20 Days Ahead	−0.132**	0.417***
	(0.059)	(0.060)
21 - 27 Days Ahead	−0.210***	0.497***
	(0.064)	(0.063)
28 - 55 Days Ahead	−0.225***	0.655***
	(0.054)	(0.056)
56 + Days Ahead	−0.231***	0.722***
	(0.057)	(0.057)
Gender Filled Female	0.144***	0.184***
	(0.041)	(0.032)
Gender Filled Male	0.053	0.213***
	(0.043)	(0.033)
N	15,190	10,354

Column 1 displays the results of a Poisson regression of number of inquiries after initial rejections on trip and guest characteristics. Column 2 displays the results of a regression of number of simultaneous inquiries on guest and trip characteristics. "Initial Con." refers to the number of inquiries a searcher sent simultaneously at the start of search. "Rev." and "Exp." referred to whether the guest was reviewed or had a prior trip, respectively. "Days Ahead" refers to the number of days before the check-in date at which the searcher entered the market. "Filled Female" and "Filled Male" refer to cases when there was information on the gender of the searcher. The estimation sample consists of all non-foreign language inquiries sent by guests in City X between January 2012 and July 2013.

Table 4: Simulation Parameters

Calibrated Parameter	Value
Mean Hours To Book	35.08
Share of Listings Unavailable	0.22
Mean Time of Calendar Update (Days Before Checkin)	37
Mean Number of Listings Viewed	63
Probability of Leaving After Non-Rejection	0.265
Gamma (Determines Correlation of Browsed Listings)	0.5

The parameters above were calibrated to match the analogous moments in the data.

Table 5: Simulation Results

	Data	Baseline
Share Contacting	0.50	0.53
Share Booking	0.31	0.27
Mean Revenue	90.43	87.37
Mean Cons. Surp.		72.32
Sim. Inq. per Contacter	1.43	1.44
Seq. Inq. per Contacter	0.49	0.50
Share Screen Rej	0.29	0.31
Share Stale Vac. Rej	0.16	0.13
Share Cong. Rej	0.03	0.04

Column 1 displays the outcomes that actually occurred for City X and the week of April 10, 2013. Column 2 displays the analogous moments computed using the simulation. Share contacted is the share of searchers that sent at least one inquiry. Share booked is the share of searchers that booked a room. "Sim. Inq. per Contacter" is the average number of simultaneous inquiries sent. "Seq. Inq. per Contacter" is the average number of sequential inquiries sent. "Share Screen Rej", "Share Stale Vac. Rej", and "Share Cong. Rej" refer to share of inquiries due to screening, stale vacancies and congestion respectively.

Table 6: The Effect of Frictions in Equilibrium

	Baseline	No Rej.	Full Set	NR + FS	Max CS
Share Contacting	0.53	0.50	0.84	0.66	0.48
Share Booking	0.27	0.37	0.39	0.48	0.48
Mean Revenue	87.37	120.83	133.35	172.10	149.81
Mean Cons. Surp.	72.32	80.26	130.88	144.47	159.88

The above table displays the average outcome of 100 simulations for each counterfactual scenario. Column 2 shows results in which searchers cannot send inquiries to hosts who would reject them for any reason. Column 3 shows simulation results if searchers have all options in their consideration set. Column 4 shows results in which searchers have all options in their consideration set other than those that would reject them. Column 5 gives outcomes from the solution to the assignment problem which maximizes consumer surplus.

Table 7: The Effect of Rejections in Equilibrium

	Baseline	No Screen	No Cong.	No Stale	No Rej.
Share Contacting	0.53	0.52	0.53	0.53	0.50
Share Booking	0.27	0.34	0.27	0.29	0.37
Mean Revenue	87.37	111.92	88.80	94.49	120.83
Mean Cons. Surp.	72.32	81.78	72.59	74.55	80.26

The above table displays the average outcome of 100 simulations for each counterfactual scenario. Columns 2-4 shows results from simulations in which individuals cannot send inquiries to hosts who would have rejected those searchers due to screening, congestion and stale vacancies respectively. Column 5 shows results in which searchers cannot send inquiries to hosts who would reject them for any reason.

Table 8: Effects of Marketplace Policies

	Baseline	Best Rank	Personal Rank	Hide High Prob	More Search	Pause Overlap
Share Contacting	0.53	0.59	0.60	0.53	0.53	0.53
Share Booking	0.27	0.29	0.29	0.27	0.27	0.27
Mean Revenue	87.37	89.29	91.56	87.07	88.50	90.01
Mean Consumer Surplus	72.32	79.49	81.21	71.06	70.13	71.41
Simultaneous Inquiries per Contacter	1.44	1.46	1.47	1.42	1.60	1.43
Sequential Inquiries per Contacter	0.50	0.55	0.56	0.48	0.53	0.48
Share Screening Rejections	0.31	0.29	0.29	0.28	0.31	0.31
Share Stale Vacancy Rejections	0.13	0.16	0.17	0.13	0.13	0.13
Share Congestion Rejections	0.04	0.05	0.05	0.04	0.03	0.02
Mean Search Cost	3.36	5.96	6.09	5.01	5.67	5.02

The above table displays the average outcome of 50 simulations for each counterfactual scenario. Column 2 shows results from the simulation in which all searchers saw the highest average utility properties in search. Column 3 shows results from the simulation in which all searchers saw a personalized ranking. Column 4 shows results if the propensity of searchers to simultaneously search was doubled.

Table 9: Aggregate Matching Function

	Log(Bookings)
Constant	-1.689^{***}
	(0.116)
Personalized Algorithm	-0.035
	(0.164)
Log(Listings)	0.226^{***}
	(0.012)
Log(Searchers)	0.831^{***}
	(0.012)
Personalized Algorithm * Log(Listings)	0.061^{***}
	(0.017)
Personalized Algorithm * Log(Searchers)	-0.042^{**}
	(0.017)
Observations	500
R^2	0.954

The above table displays the average outcome of 10 simulations for each counterfactual scenario. Column 2 shows results from the simulation in which all searchers saw the highest average utility properties in search. Column 3 shows results from the simulation in which all searchers saw a personalized ranking. Column 4 shows results if the propensity of searchers to simultaneously search was doubled.

Table 10: Experimental vs Market Level Effects of Better Search Rankings

	AB	Market
Change in Share Contacting	0.086	0.060
Change in Share Booking	0.035	0.018
Change in Mean Revenue	5.802	1.920
Change in Mean Consumer Surplus	12.079	7.161

The above table displays the average outcome of 50 simulations for each counterfactual scenario. Column 1 shows the treatment effect of seeing the "Best Rank" search algorithm in a 50% experiment at a searcher level. Column 2 shows the actual effect of the "Best Rank" policy if all searchers were to see it.

A. Appendix: Rejection Classification

This Appendix describes how to use a regularized logistic regression to classify the text of communications between hosts and guests. I divide each message into individual words and combinations of words (n-grams).[31] I use n-grams as features in a regularized logistic regression (RLR) that predicts whether a message a rejection or not.

The process of classification requires two steps: training and prediction. The procedure requires definitive cases when a message is either a rejection or not a rejection. A definitive case of a non-rejection occurs when a thread eventually leads to a transaction. A definitive case of a rejection occurs in a subset of messages for which hosts label that the room is "Not Available". I choose the top 30 thousand n-grams in my sample in addition to features for question marks and the number of sentences for my classifier. Prior to classification, I correct the text for common misspellings and determine the language of the text (See Appendix for details).

The RLR is estimated using 500 thousand labeled messages. The purpose of using regularization is to reduce over-fitting that might occur when so many features are included. The RLR penalizes the model for having too many non-zero coefficients. The classifier places high weight on n-grams such as "Sorry", "Unfortunately", "Is Occupied" for rejections. I test the validity of the procedure using two methods. First, I use the estimated model to classify a hold-out sample of labeled data. The classifier achieves a type 1 error of 2.6% and a type 2 error of 2.0%. That is, 2.6% of non-rejections are labeled as rejections and 2.0% of rejections are mistakenly labeled as non-rejections. The second validation I use is a manual inspection of 500 previously unlabeled messages. The classifier has a type 1 error of 3.4% and a type 2 error 8.1% in that subsample.

I combine classifications from the NLP classifier with cases when the response is discernibly through other methods. The final classification works as follows. If a contact led to a booking or if it was labeled as accepted by the host then it is classified as 'not rejected'. If a response was labeled by the host as a rejection or if there was no response within the week after the inquiry then the contact is classified as a rejection. If a response is classified as having a foreign language then it is not used in the analysis.[32]Lastly, if the contact does not fit into any of the above categories, the NLP classifier is applied to the first (or in some cases second) response by a host to a guest. In total, 49% of all inquiries were rejected. Of all contacts classified as rejections, 37% were cases in which a host did not respond, 30% were host classified rejections after an inquiry and 32% used the NLP classifier.

[31]For example, "car" is a 1-gram, "my car" is a 2-gram and "my fast car" is a 3-gram.

[32]An inquiry with 3 or more words was tested for being in a foreign language if it had more than 30% of words that were not in the English dictionary and were not common misspellings. The message text was run through a language detection algorithm in Python called "guess-language" (http://code.google.com/p/guess-language/). If the algorithm guessed a valid non-English language then the inquiry was classified as being in a foreign language. A 50% cutoff was used for inquiries with 2 words.

B. Appendix: Derivation of Sample Weights

Table B.1: Determinants of Sampling Weights

Private Room	-0.324^{***} (0.010)
1 - 4 Reviews	0.778^{***} (0.012)
5 - 9 Reviews	1.269^{***} (0.013)
10 - 19 Reviews	1.795^{***} (0.013)
20 - 39 Reviews	2.182^{***} (0.014)
40 - 80 Reviews	2.563^{***} (0.021)
80 + Reviews	3.479^{***} (0.036)
Price (50 - 74) USD	0.223^{***} (0.016)
Price (75 - 99) USD	0.292^{***} (0.017)
Price (100 - 149) USD	0.242^{***} (0.018)
Price (150 - 199) USD	0.526^{***} (0.019)
Price (200 - 299) USD	0.399^{***} (0.022)
Price (300 - 499) USD	0.349^{***} (0.026)
Price (500 +) USD	-0.096^{**} (0.044)
Person Capacity	0.049^{***} (0.002)
Num. Pictures	0.015^{***} (0.0004)
Listing Tenure (Days)	-0.002^{***} (0.00002)
Neighborhood FE	YES
Num. Searchers	71,781

The above table displays the coefficients on listing characteristics which predict whether that listing is a part of a searcher's consideration set. The model is a conditional logistic regression.

C. Appendix: An Urn and Balls Model of Matching

To see how search frictions affect the matching rate consider the simple urn and ball model of matching described in Petrongolo and Pissarides (2001). Suppose there exists a mass, G, of identical guests sending 1 inquiry each to a mass, L, of identical listings that can only transact with one guest each. The resulting number of matches produced is $L(1 - e^{-G/L})$. If an all-knowing social planner was matching guests and listings then the total amount of matches would be $\min(G, L)$. To simplify further analysis, suppose that $L < G$. Therefore, the total inefficiency in the marketplace is a function of the failed matches, $Le^{-G/L}$. Inefficiency in this model comes from a coordination friction, where some listings reject guests because they are already booked. The welfare costs of the friction in this model are a function of the match utility of unmatched agents who could have been matched and the costs of wasted search.

Another friction that exists on Airbnb is that some listings are not actually available to anyone. Suppose that there is a mass of stale listings, U, which are not interested in transacting although they are visible to guests. The amount of matches in the marketplace becomes $L(1-e^{\frac{-G}{L+U}})$, with the amount of inefficient search equal to: $Le^{\frac{-G}{L+U}} > Le^{-G/L}$. Stale listings increase inefficiency due to additional mismatch and wasted search costs. Stale listings could be even more important in dynamic matching markets because the likelihood of a stale listing being contacted increases as non-stale listings are booked.

Lastly, there are some hosts who are selective about which guests and trips they are willing to host. Suppose that listings are only willing to transact with a random subset of searchers. Let there be a mass of K selective sellers who are willing to transact with a random guest at a rate c. The remaining L - K non-selective sellers are willing to transact with anyone. The aggregate number of matches in the marketplace will be $(L-K)(1-e^{\frac{-G}{L+U}}) + K(1-e^{\frac{-cG}{L+U}})$ and the number of inefficient inquiries is, $Le^{\frac{-G}{L}} + K(e^{\frac{-cG}{L}} - e^{\frac{-G}{L}})$, where the first term represents coordination and stale vacancies and the second term represents screening frictions. In turn, the cost of screening frictions depends on the share of listings which are selective, $\frac{K}{L}$ and on the selectivity of the listings, c.

The frictions in an urn and balls model all operate through the rejection channel. When inquiries are rejected, search effort is wasted and potential transactions do not happen. A full model, such as the one of the paper, would account for the ability of searchers to conduct sequential and simultaneous search. Furthermore, such a model would allow for some searchers to leave after being being accepted for a variety of reasons. Nonetheless, most of the intuition from an Urn and Balls model will hold in more realistic models of matching. Rejections will occur, will be costly to searchers and will slow the rate of match formation. The quantitative impact of frictions must, however, be determined within a more realistic model that accounts for heterogeneity, simultaneous search and dynamics.

D. Appendix: Robustness of Results to Random Utility Assumptions

A concern with the consumer surplus maximizing outcomes in the model is that they are driven by a misspecification of the idiosyncratic utility term. If listings crowd each other out in characteristic space or if there is measurement error in consideration sets then my estimate of the random utility error would be too large. Below, I display the results of the consumer maximizing outcome in which I lower the standard deviation of the random utility error. A misspecification of the error of standard deviations by 5% and 10% barely changes booking rates. Even if the standard deviation of the error term was off by 25%, the optimal outcome would result in more booking than is observed in the data. On the other hand, inference about the consumer surplus from the optimal allocation is more sensitive to the standard deviation of the error. Consumer surplus drops by more than 50% if the true utility error standard deviation was 75% of the estimated standard deviation error.

Table D.1: Robustness of Consumer Surplus Maximizing Results

% of Error Sd	Share Booked	Revenue Per Searcher	Consumer Surplus
95	0.46	140.09	135.60
90	0.45	130.29	115.39
75	0.37	93.66	60.93
50	0.22	25.67	8.20

The above table displays the outcomes if the standard deviation of the random utility error was decreased by 5%, 10%, 25% and 50%.