Search, Selectivity, and Market Thickness in Two-Sided Markets

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September 10, 2018

Abstract

This paper investigates search and matching in online marketplaces, emphasizing how user behavior responds to the presence of others on the platform, which I call "market thickness". Unlike standard settings in which firms typically benefit from increasing their customer base, in two-sided markets, changes in market thickness can induce complex effects in matching due to the endogenous adjustment of search and selectivity. I study search and matching behavior in the setting of an online dating application. Motivated by the observed correlation between individual's selectivity and the number of potential matches and competitors in this market, this paper causally measures the impact of market thickness on behavior and explores its implications for platform design. I design and implement a field experiment that generates engineered variation in the beliefs of platform participants about the number of potential matches (market size) and number of competitors. Consistent with intuition and observational patterns, the experiment shows that individuals become more selective when they believe they have more potential matches, and less selective when they believe they have more competition. The effect of changes in selectivity on matching is however an equilibrium outcome. I therefore use the exogenous variation generated by the experiment to identify the parameters of a microfounded model, which then allows me to estimate the equilibrium and evaluate platform-design-linked counterfactuals. I find that in some types of markets, increasing platform membership for both sides of market (e.g. increasing both men and women) leads to fewer matches, and increasing one side of the market (e.g. the number of women) may not significantly improve match quality for the other side of the market (men). However, platforms may be able to mitigate the negative effects of increasing either both sides or one side of the market through policies that influence selectivity.

1 Introduction

This paper investigates search and matching on decentralized platforms with a goal of improving platform design. Decentralized platforms are two-sided marketplaces in which individuals search

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to find matches, which are formed only upon the explicit agreement of both parties in response to proposals. In contrast, centralized markets assign matches to agents in a centralized mechanism, obviating both the need for search, and the uncertainty from agents' perspective of whether match proposals will be accepted. Decentralized platforms are ubiquitous. An example is job search. Workers and firms search to fill vacant jobs, and it is costly for workers to apply to jobs and for firms to conduct interviews. Another example is dating. In order to go on a date, the man or woman needs to propose a date, and in order for the date to occur, both the man and woman need to agree. Since matches are determined through an agent's search behavior, understanding the nature of search is critical to platform design. I design and implement a field experiment on a popular dating app, which I combine with a microfounded, econometric model of search in order to evaluate the impact of platform size and design on matching.

Understanding agent behavior in two-sided markets is challenging in that an agent's actions are based off beliefs about other agents' behavior. Because search and match proposals are costly, agents are what I call *strategically selective*. An agent's decision to propose a match with another agent depends on (1) his beliefs about whether the other agent will accept the match, and (2) the likelihood that he will find another match if the current potential match is not realized. The likelihood of finding another match depends on the availability of other agents on the platform, which has been referred to in the literature as *market thickness*. Specifically, market thickness is comprised of two constructs: the number of potential matches, which I call "market size", and the number of competitors, which I call "competition size".[1] For example, a seller's market size is the number of buyers, and competitor size is the number of other sellers on the platform; thus, the seller's market thickness is the number of buyers *and* the number of sellers. I refer to an increase in market thickness as an increase in both elements of the tuple (i.e. an equal increase in both buyers and sellers). The endogenous adjustment of search, selectivity, and matching to contexts with varying market and competition size forms the core essence of behavior on a two-sided platform. I explore this dependence using data from a large, worldwide dating application.

Using historical observational data from this dating app, I find a strong correlation between market thickness and selectivity.[2] Individuals who have a larger market size seem to be more

[1] More specifically, market thickness is a tuple: (market size, competition size).

[2] I define selectivity to be the threshold at which an individual uses to decide whether to propose a match. Individuals who are more selective have a higher threshold; they are more likely to propose a match with high quality

selective, and users who have more competition seem to be less selective. These raw, stylized patterns in the data stand in contrast from the conventional wisdom in the theoretical literature on market thickness and matching. Broadly speaking, the theory suggests that markets with more potential matches generate more and better matches. Intuitively, a market with more potential matches has a larger potential choice set, so it is more likely to have an agent who is willing to match. Conversely, when an agent has more competition, he is less likely to find a match and conditional on matching, the matches are lower quality. However, this intuition does not hold when individuals can endogenously adjust their search and selectivity in response to market and competition size. In this paper, I show that such endogenous adjustment is occurring; and that allowing for the adjustment in a microfounded model of search and matching can rationalize these patterns observed in the historical data.

In contrast, the extant literature has either focused on centralized matching contexts that abstract away from search and selectivity (Gale and Shapley 1962; Abdulkadiroğlu et al. 2005; Roth and Peranson 1999); do not model search as endogenous to market thickness (Halaburda, Jan Piskorski, and Yildirim 2017; Kanoria and Saban 2017); abstracted away from search (Rochet and Tirole 2003; Hagiu 2006); or studied matching in the aggregate, abstracting away from these issues (Petrongolo and Pissarides 2001). In Section 2, I review these this literature in more detail.

There are challenges to be confronted in order to formally investigate the effect of market thickness on matching. First, one needs high frequency, individual-level data. In many contexts, only market-level outcomes are observed, or if data at the individual level is available, typically only the match is observed. For example, in job search data, the researcher can typically observe only the job that is accepted, not the jobs that were rejected, the applications the worker sent, or the interviews that were conducted. One of the points of this paper is to present a new dataset, which contains microlevel data on search. I can observe the sequence in which profiles were viewed, to whom match proposals were sent, and the matches that were realized. Second, quantifying the causal impact of market thickness on search behavior and matching is difficult because matching is confounded with the endogeneity of market thickness. The worry is that heterogeneous agents may self-select into locations of varying market thickness depending on their propensity to search or value for finding a match. For example, people with a high propensity to search may self select

users and less likely to propose a match with lower quality users, compared to a less selective individual.

into locations with many people. It is difficult to estimate the causal effect from observational data alone due to the challenge of finding exogenous variation in market and competition size. Third, measuring the effect of market thickness requires a broad support of market and competition size in the data. That is, to measure the heterogeneous effect of market thickness across small and large markets, we need to see exogenous variation in market thickness across a variety of different markets.

I address these problems using a three-fold strategy: (1) develop and implement a randomized controlled trial that generates exogenous variation in beliefs of market thickness in 2 neighboring countries served by the app, (2) track each individual's searches and outcomes, and (3) estimate a structural model of search and selectivity to analyze counterfactuals involving market thickness. The dating platform is designed such that an agent views profiles sequentially, and he must either `like` or not `like` the agent before viewing the next profile. In this setting, a `like` is the action that an agent takes to propose a match. The sequential nature of the search process ensures that I am able to observe each search instance. For each agent, I observe not only the experimental variation but also each profile he views, whether he `liked` the profile, and whether they match.

The experiment shows that beliefs in market thickness generate changes in behavior. While individuals, on average, are not significantly changing their search intensity, When users believe their market size increases by 50%, they become 3% less likely to like low quality users and 2.8% more likely to like high quality users. In contrast, when they believe they have 50% more competition, they become 2.3% more likely to like low quality users, and 4.5% less likely to like high quality users. Due to this change in selectivity, individuals get fewer matches when they think they have a larger market size, and more matches when they think they have more competitors. However, the effect of market thickness on matching must be evaluated under an equilibrium, as matches are equilibrium outcomes.

To find equilibrium implications when the actual, rather than beliefs about, market thickness changes, I develop a dynamic model of sequential search that is expanded to handle two-sided markets through incorporating beliefs about other agents' actions on the platform. By giving the model an explicit role for beliefs, I can leverage the exogenous variation in beliefs about market thickness from the experiment to estimate the parameters in the model. In this sense, this setup creates a bridge between experimental and theory-driven components of my investigation.

While beliefs are a key part of this model, beliefs also introduce complications in estimation. The observed agents' search behavior and matches are the outcomes of a Bayesian Nash Equilibrium of a dating game between men and women. In this equilibrium, agents have beliefs about other agents' actions, the likelihood another agent of a given quality likes them; and beliefs about quality of profiles they will see. Given these beliefs, they search and decide who to propose matches with optimally. However, when there are many agents in the game, solving the equilibrium becomes computationally challenging. I obviate some of the challenges in inference by borrowing from the literature on two-step estimation methods (Hotz and Miller 1993; Bajari, Benkard, and Levin 2007; Aguirregabiria and Mira 2007). The detailed data on agent states, along with assumptions on agent rationality, allow me to estimate equilibrium beliefs about other agents' actions in the first stage. This enables inference of a complex dynamic game at lower computational costs. Rich variation in data from prior to the experiment facilitates making the first-stage estimation flexible to the extent possible.

The estimates from the model show that the effects of market thickness are consistent with the experimental results, and are heterogeneous across market types and gender. An increase in market size causes agents to become less likely to `like` other agents, especially agents of low quality types, and the magnitude of this effect is larger for men than women. When competition increases, both men and women become more likely to `like` lower quality type profiles, and slightly less likely to `like` higher quality type profiles. Competition has a larger effect in large markets, and the effect is larger for women than men. The intuition behind this difference in magnitude is that in markets with fewer people, the users that an individual `likes` are more likely to see his profile, than if he were in a larger market. As a result, an increase in competition has a smaller marginal effect on the likelihood that the user's profile is seen, as compared to a larger market. The fact that men, on average, search less than women, may also explain why the effect of competition is larger for women than men; since men view fewer profiles, the chance that he sees a specific woman's profile decreases.

Given the estimates from the model, I simulate how changes in market thickness impact an agent's number of matches, the average quality of the matches, and the probability that the agent finds a date. Specifically, I focus on two main counterfactuals that are often implemented by platforms. The first is growing the platform by increasing market thickness (e.g. increasing the number of men and women). Second is rebalancing the sides of the market. Platforms, especially online dating sites, often face an asymmetry in the number of agents on each side of the market. To rebalance the market, platforms may selectively target growth for one side of the market (e.g. increasing the number of women on the app). Both of these counterfactuals are facilitated by targeted advertising or fee subsidization.

I find that, counterintuitively, adding more members to both sides of the market generally decreases the number of matches that each individual gets through increasing selectivity. When the number of men and women increase by 25%, men and women in small markets get 12% and 18% fewer matches, respectively, and 0.4% more and 6% fewer matches for men and women in large markets. When an individual has a larger market size, he becomes less likely to `like` lower quality users, which are the individuals who are most likely to like him back. In particular, since men react more to an increase in market size, as compared to women, men become much less likely to like lower quality women, and women respond by becoming more likely to like lower quality men. The overall outcome of this effect is fewer matches because men `like` fewer women.

The second counterfactual is "gender gating": the platform selectively targets one side of the market to join the platform, or equivalently, disincentivizes the other side from joining. I find that, contrary to theoretical predictions, increasing the number of agents one side of the market does not always significantly increase match quality for agents on the other side of the market. When there is a 25% increase in women in small markets, men, on average, get more matches, but conditional on matching, the average match quality decreases by 0.6%, and 7% fewer men find dates. On the other hand, in larger markets, men get more matches and are more likely to find a date, but experience only a 1.6% increase in match quality. The difference between the outcomes in small and large markets is due to the difference in the direct effect of competition. Women become less selective in large markets when they have more competition, so they are more likely to accept a lower quality match.

These counterfactuals imply that limiting platform membership can increase matching outcomes for some users. However, the platform monetizes through premium users, so limiting membership may mean a loss in potential revenue. Therefore, I evaluate how the platform can improve matching outcomes under an increase in market thickness and gender gating. Since the changes in outcomes are driven by changes in selectivity, one of the levers that this platform can pull to influence selectivity is a limit on how many match proposals an individual can send. I show that doubling the limit on the number of match proposals for all users when market thickness increases, and doubling the limit for women only under the gender gating policy, can mitigate some of the negative effects of market thickness and competition for women, respectively.

In summary, this paper makes four contributions. First, I bring new data, combined with a field experiment and a model that simulates counterfactual outcomes, to analyze search and selectivity on a two-sided matching platform. The existing empirical literature on this topic has not treated the endogenous adjustment of search in such platforms in a satisfactory way. Second, the paper's results demonstrates that search and selectivity are endogenous to beliefs about market thickness, and presents a microfounded model that links search and selectivity to market thickness. This contributes to the literature on matching that has emphasized the importance of linking the aggregate number of agents on each side to the total matches formed, such as in the matching function[3], to microfoundations. Third, using the individual-level effect of beliefs about market thickness on search behavior and through the simulation of counterfactuals, this paper re-examines the conventional wisdom in the matching markets literature that individuals are better off when they have more potential matches. While the magnitude of the effect is specific to this empirical setting, my analysis suggests that it is possible for agents to find a better match when they have more competition. When designing the platform, I show that is important for firms to consider how agents react to market thickness in their setting rather than assume competition (market) size strictly reduces (increases) match quantities and qualities. Fourth, the paper integrates variation in beliefs generated from a field experiment, into a microfounded model, which then incorporates those exogenous beliefs to estimate the parameters. The variation in beliefs not only extends transparently to the model, but also is straightforward for the firm to implement, as experimentally changing market thickness is difficult to do. I show that changing beliefs about market thickness is sufficient to influence behavior and to estimate the model. This strategy of inducing belief variation in an experiment and incorporating it into a theory-driven model for identification may be useful in other contexts as well.

The remainder of the paper is organized as follows. First, I review relevant literature and its

[3]See Petrongolo and Pissarides (2001) for a comprehensive literature review.

relation to this paper. In Section 3, I describe the empirical setting and the motivating data patterns in more detail before presenting the experimental design in Section 4. Section 5 summarizes the data and presents the reduced-form results from the experiment. In Section 6, I propose the model of search and selectivity that is based on sequential search foundations. Estimation details are discussed in Section 7. The results of this model are shown in Section 8. Section 9 illustrates the counterfactuals produced from the estimated parameters. Section 10 concludes by summarizing the key findings and directions for future research.

2 Relevant Literature

This paper contributes to three separate but related literatures: job search, matching markets, and consumer search.

2.1 Job Search

Market thickness primarily has been studied in the labor literature as the matching function. This function relates the aggregate number of unemployed workers U and vacant job openings V to the number of jobs filled by $M = m(U, V)$. The idea of this function is to create an aggregate function that captures frictions, such as heterogeneity, congestion effects, etc, rather than modeling out all these factors separately. Many papers have either made functional-form assumptions about $m(U, V)$, (Burdett, Shi, and Wright 2001; Diamond 1982; Acemoglu and Shimer 1999; Buchholz 2016; Howitt and Mcafee 1987; Pissarides 1984), or empirically estimate the returns to scale of the matching function (Coles and Smith 1998; Blanchard and Diamond 1994; Gregg and Petrongolo 1997; Bleakley and Fuhrer 1997; Burda and Profit 1996).[4]

My paper is related to a subset of papers in the matching function literature that go beyond aggregate unemployed worker and job openings, by focusing on the microfoundations that may contribute to the shape of the matching function. While the simplest matching function only includes aggregate unemployed workers and vacant jobs, Petrongolo and Pissarides (2001) state that there has been literature focused on finding other variables that affect the match rate, such as search intensity. For example, Stevens (2007) theoretically develops a new matching function where search

[4]See Petrongolo and Pissarides (2001) for a comprehensive survey of matching function literature.

intensity directly affects the match rate. Pissarides (1984) develops a two-sided search model and theoretically shows that when both sides of the market search, it creates too much employment due to low search intensity in equilibrium.Gautier, Moraga-González, and Wolthoff (2007) empirically estimate a structural model of search using wage data from the Dutch labor market to derive the socially-optimal distribution search intensity. They find simultaneously creating more vacant jobs and increasing search intensity can create large welfare gains. While search intensity is clearly an important factor in determining match rates, to the best of my knowledge, no paper in this literature has been able to observe individual-level search and relate it to market thickness. Therefore, my contribution to this stream of literature is to shed light on the matching function's microfoundations. This paper demonstrates how the number of choices (analogous to aggregate job openings) and the number of competitors (analogous to aggregate unemployed workers) affect and selectivity, which may guide future work in understanding the "black box".

2.2 Matching Markets

There is a rich theory literature on matching markets. Much of the theory literature focuses on competition, pricing, and critical mass using simplifying assumptions of matching and consumer search. This area of research focuses on platform participation rather than matching. To simplify the matching process, the number of matches on a platform is commonly assumed to be a fraction of the product of the number of agents on each side (Rochet and Tirole 2003). There are also theory papers that focus on search and matching. Halaburda, Jan Piskorski, and Yildirim (2017) build a theoretical, microfounded model in a setting where agents propose a match to the agent with the highest match value. The authors show that increasing choice for all agents on the platform has two separate effects. It increases the chances of matching because the agent is more likely to find an attractive match (choice effect). On the other hand, because everyone has more choice, the other agent is less likely to accept the match, but she also has more choice (competition effect). Kanoria and Saban (2017) theoretically evaluates platform design in relation to which side of the market should send match proposals. In contrast to this literature, my paper empirically examines the role of more agents on the platform in settings where agents engage in costly search to evaluate a subset of other agents and are strategically selective about who they propose to match with. Shimer and Smith (2001) build a model of search on a decentralized platform where agents have heterogeneous productivity. The authors show that the equilibrium in decentralized market is inefficient and how the thick market externality and congestion have differing effects for agents of different productivity levels.

There are limited empirical papers on search and matching on platforms. One stream of literature focuses on platform growth. Tucker and Zhang (2010) implement a field experiment where a two-sided network advertises information about sellers and/or buyers and examine the impact the treatment has on entry. They find that if sellers do not know how many buyers are in the market, sellers are more likely to enter the market when there are more sellers as they believe more sellers mean more buyers. Chu and Manchanda (2016) study cross and direct network effects on an e-commerce platform and find that growth in buyers is primarily driven by growth in sellers. Cullen and Farronato (2015) study how a two-sided platform can create matches, even when supply and demand on the platform are not stable. They find that on TaskRabbit, supply is much more elastic than demand, so the firm should focus on increasing demand rather than supply. My paper builds on these findings by looking at not only how the two sides affect only how many matches are made, but also match quality, which is not focused on in their setting. In addition, my paper builds on this area of research through (1) independently measuring the effects of more agents on the platform, as the treatments for market size and competition size are independent, and (2) studying outcomes for agents once on the platform, rather than the decision to join.

Another stream of empirical matching markets literature focuses on matching outcomes Gan and Li (2004) focus on the economics job market and find evidence for a positive effect of market thickness on the probability of matching at the aggregate level, but are not able to observe the individual search process. Fradkin (2015) creates a model of search on Airbnb and focuses on how ranking algorithms can increase matches in the marketplace. My paper is different from these in that I highlight the role of strategic selectivity; the decision to propose a match depends on the belief about how likely the other agent is to accept, which has not been emphasized.

There is a subset of empirical papers that focus on online dating in particular. Hitsch, Hortaçsu, and Ariely (2010a) use data from an online dating website to measure the stability of matches. They find that the predicted stable matches are similar to matches made on the website. There has also been research on preferences in dating. Fisman et al. (2006) measure differences in preferences between men and women through a speed dating experiment, and Lee and Niederle (2014) show that preference signaling increases an individual's match rate through a field experiment on a Korean dating website. Hitsch, Hortaçsu, and Ariely (2010b) estimate mate preferences by modeling a person's probability of contacting another person with a threshold-crossing rule. However, these aforementioned papers have not studied the role of market thickness in influencing matching outcomes. In addition, Hitsch, Hortaçsu, and Ariely (2010b) find no evidence of strategic behavior in their setting, but this paper shows that information about market thickness is able to change the type of people that a user proposes a match to, such suggests strategic selectivity in this setting.

Lastly, the stable matching literature often ignores the search process as it is focused on centralized markets, where search is not present. There is, however, a subset of the matching literature that focuses on developing theoretical models of search and matching. In these papers, agents follow a sequential search model where the agent's reservation value is depends on search costs, arrival rates, and the distribution of quality of agents on the other side of the market (see Burdett and Coles (1999), Adachi (2003), and Mortensen (1982) for examples). To the best of my knowledge, there does not exist any theoretical or empirical literature that studies matching through the lens of strategic selectivity and the availability of other agents on the platform.

2.3 Consumer Search

Many economics papers in consumer search do not involve two-sided matching, as purchasing a product is not a two-sided decision. Behavioral economics and psychology have explored the role of the number of choices on search and purchase behavior. Reutskaja et al. (2011) study how the computation processes consumers use during search change when the number of options change. They conduct a lab experiment where hungry subjects have three seconds to choose a snack out of sets of 4, 9, or 16 snacks. They have subjects rank all snacks prior to the experiment. Using eye-tracking technology, they find that as the set size increased, subjects searched across more snacks, but because of the time constraint and only being able to see a subset of the choices, they made less optimal choices. Iyengar and Lepper (2000) show that subjects often postpone choice, or do not make a choice at all, when the choice sets are large. Diehl and Poynor (2010) find that individuals are less satisfied with their purchases when the product is selected from a smaller selection, indicating they have higher expectations about match values they can attain in a larger

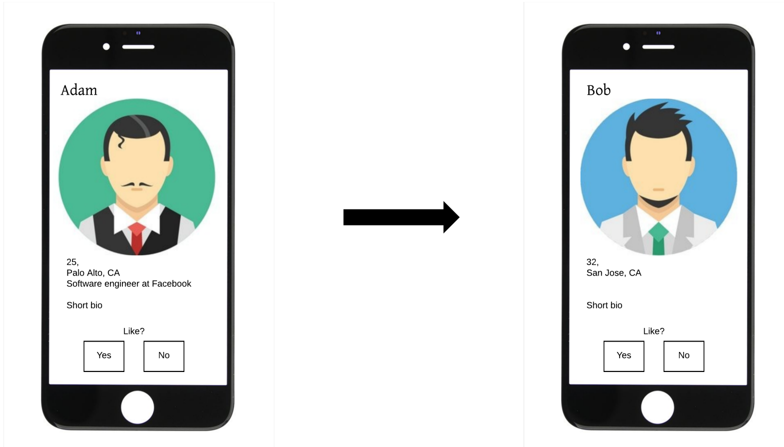

Figure 1: Example layout of the app. When the user opens the app, she is first presented with Adam's profile. The profile includes pictures, age, location, and a short bio. If the user does not `like` Adam, then she is shown the next profile, Bob.

set. This paper contributes the literature on consumer search by building on sequential search models and extending them to allow for (1) two-sided matching decisions and (2) the number of choices.

3 Empirical Setting

The setting of this paper is a mobile online dating application that has millions of active users worldwide. The types of people that use this app are mainly heterosexual adults between ages 20 to 30. Based on a user's gender, age, and distance criteria, the app serves other agents' profiles one at a time. Each profile consists of a name, pictures, and a short bio. Information such as age, occupation, and education may also be displayed.

A user may view each profile only once. Once shown the profile, he must decide whether to anonymously `like` or not `like` that profile. In this context, a `like` is defined as an action that the user takes to propose a match. A match occurs when two users mutually `like` each other. If he chooses not to `like`, then another agent's profile is displayed. For the remainder of this paper, I refer to "`like`" and "not `like`" as these actions, unless specified otherwise. Once an agent chooses to not `like` a profile, he will never be shown that profile again. Messages can only be exchanged between matched users.

3.1 Design

Figure 1 illustrates the layout of the app. When the agent opens the app, she will be shown a profile. In this example, she sees "Adam"'s profile. She then decides whether to `like` Adam. If she either does not `like` Adam or does `like` Adam but Adam has not `liked` her back, then the profile will immediately serve her the next profile, "Bob". However, if she does `like` Adam and Adam has already liked her, then she will get a notification saying she and Adam have matched, after which she and Adam can exchange messages. Note that matches may not occur instantaneously, i.e. Adam does not see and `like` her profile until the next day.

3.1.1 `like` limit

The platform monetizes through a "freemium" payment plan. Users can use the app for free, but paid users get access to more features. A difference between paid premium version and the free version is the `like` limit. Free users have a limit on how many agents' profiles they can `like` within a 12 hour period, while premium users do not. I refer to $\bar{L}$ as the cap on the number of `likes`; the exact number is confidential, as requested by the firm. The analysis in this paper will be conducted on the proportion of `likes` a user has left.

Once the agent runs out of `likes`, he cannot search for the next 12 hours. Clearly, agents value not having a limit on `likes`, so they are willing to pay for the premium version. Since this limit is important for the platform's monetization strategy and is an institutional feature of the data, I take this policy into account in the model and counterfactuals.

3.2 Historical Data

The observational, historical data displays strong correlations between selectivity and market thickness. Selectivity, in this section, is measured by the individual's `like` rate, which is the proportion of profiles that he `likes` out of all the profiles he views. I use data from heterosexual app users in the same two countries the experiment is implemented in. Specifically, the sample contains over 50,000 women and 100,000 men who viewed at least one profile in a 34-day time period in 2015.

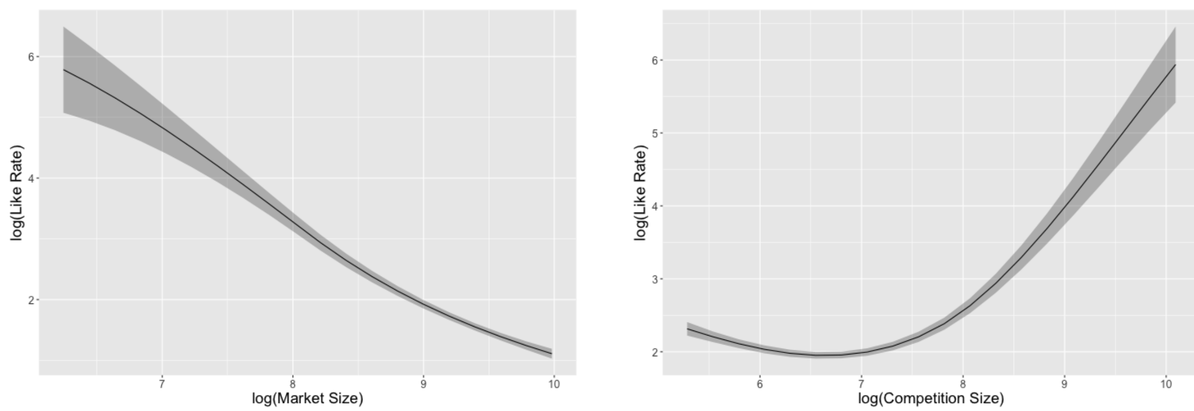

Figure 2: This figure shows the correlation between market size and competition size with selectivity, for markets with a market/competition size of at least 200. The lines are the results of a locally linear regression of an individual's `like` rate, which is the proportion of profiles that an individual `likes`, on his market size, competition size, age, and gender. The plot on the left shows the correlation between market size and the `like` rate, while holding competition constant at the average value, and the plot on the right shows the correlation between competition size and the `like` rate, while holding the market size constant at the average value. The shaded regions are 95% confidence intervals.

To explore this correlation, I estimate the following locally linear regression.

$$LikeRate_i = f\Big(\log(ms_i), \log(cs_i), age_i, gender_i\Big) + \epsilon_i \tag{1}$$

ms_i is i's average market size. Substantively, I determine a user's market size at t, the time of each profile view, which is the number of users of the opposite gender within 100 miles at t. ms_i is then the average of i's market size over time. Similarly, cs_i is i's average competition size, which is determined in the same method as market size, but is instead the number of users of the *same* gender within 100 miles.

Figure 2 displays the results from Equation 1. The `like` rate is log-transformed by an unreported base to preserve data confidentiality. The figure shows a strong correlation between both market size and competition size, with selectivity. An individual with more potential matches seems to be less likely to `like` a profile than another individual with fewer potential matches. On the other hand, an individual with more competition, on average, seems more likely to `like` another profile than an individual with less competition.

Due to the two-sidedness of matching, this correlation may result in matching outcomes that differ from the common wisdom from theory on matching and market thickness. Individuals who are more selective may get fewer matches; they may be more likely to `like` "higher quality" users who are less likely to `like` them back.

3.2.1 Endogeneity

While Figure 2 shows a strong correlation between market thickness and selectivity, these results cannot be interpreted causally. The challenge in measuring the causal effect of market thickness is that individuals self-select into markets. For example, individuals who have high propensities to search may be more likely to travel to a market with more potential matches. It could also be the case that individuals who in large cities are more selective on the dating app because they have more outside options. Thus, to measure the causal effect of market thickness on behavior, I need to leverage exogenous changes in market thickness. However, finding natural sources of exogenous variation in market and competition size in this setting is difficult, as there are network effects between the two sides of the market. That is, the number of men and women must vary independently. To illustrate, if the firm randomly increased marketing towards women only, more men may join the platform as well, making it difficult to disentangle the separate effects of market and competition size. I design and implement a randomized control trial to generate the exogenous variation needed to quantify this relationship.

4 Experiment Design

An ideal experiment exogenously changes an agent's market thickness. However, it is not practical to randomly add or remove agents from the platform, so my experiment varies information about market thickness, with the assumption that the information changes agents' *beliefs* about market thickness. Upon opening the app, a user in the treatment group sees a pop-up notification with the message "There are at least m men and w women nearby!". Users in the treatment group see varying values of m and w. I refer to the pop-up message as the *treatment*, and m and w as the *treatment values*. Figure 3 provides an illustration of the design of the pop-up message.

The focal effect measured by this experiment is *not* the difference between users who see the pop-up message and users who do not, but between users who see different treatment values. Before describing the experiment in detail, I first illustrate the intuition behind this experiment with the following. Consider an experiment where there are two types of treatment values. A user sees either a high (H) or low (L) value for the number of men and women. Figure 1 depicts all possible combinations of the treatment that the user can receive. Since the treatment values for m

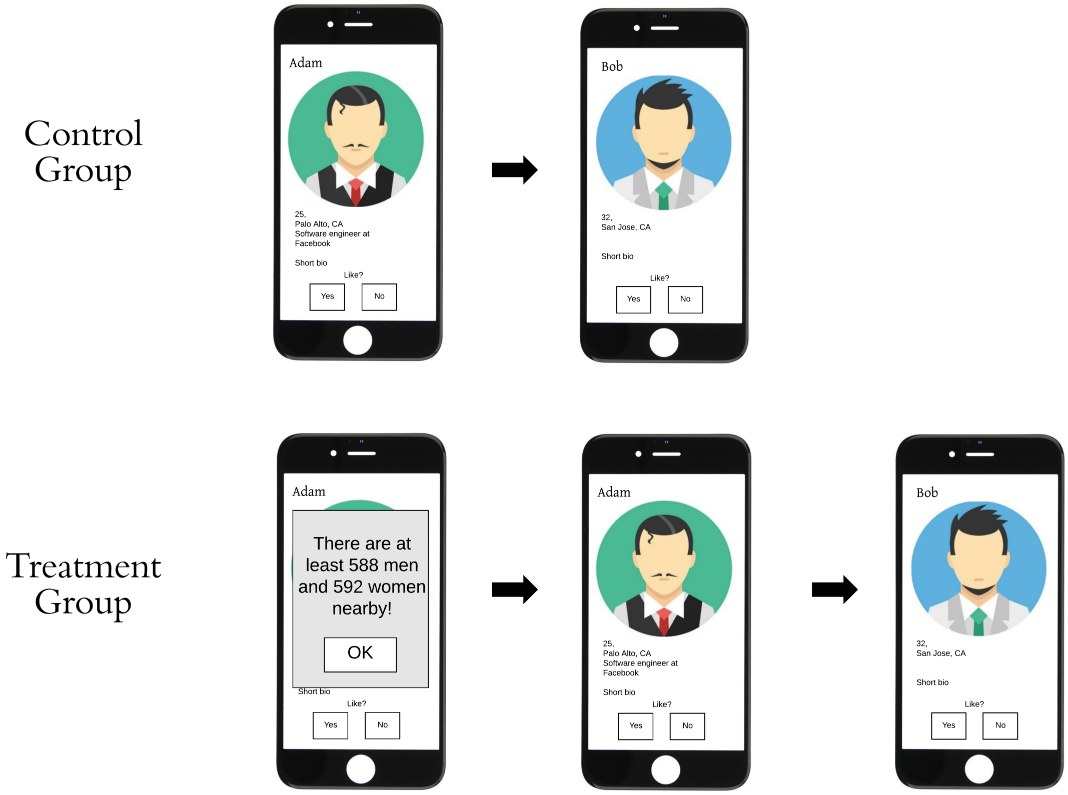

Figure 3: Example of how the treatment condition is different from the control condition. The treatment condition receives the pop-up message while control users see no change in the app.

and w are drawn independently, the user can see a high draw of m and a low draw for w, or vice versa. The average effect of market size for men is measured by comparing the difference in the outcome variable for men who see a high draw of w and a low draw of w, $E[Y_{w=H} - Y_{w=L}]$, and the average effect of competition size is $E[Y_{m=H} - Y_{m=L}]$. The effect is similar for women, except their market size is the number of men, and competition size is the number of women.

The difference between this descriptive example and the actual experiment that is implemented is that the treatment values have more levels than just H and L. The following section describes this experiment in more detail.

4.1 Treatment Values

In the ideal experiment, m and w would be randomly drawn. However, the agents must see a reasonable number of his or her market and competition sizes to ensure that experimental effects

$m = H$ $w = H$	$m = L$ $w = H$
$m = H$ $w = L$	$m = L$ $w = L$

Table 1: This table presents a simplified design of the experiment to explain the intuition behind the experiment. When the number of men and women are either H or L, here are 4 possible combinations of m and w that a treated user can be exposed to, as the treatment values m and w are drawn independently.

are not influenced by the Hawthorne effect (McCarney et al. 2007). A way that the Hawthorne effect may arise in this study is through unrealistic treatment assignments: agents may not believe the treatment values they are shown. For example, individuals who live in rural areas would not believe are 10,000 men or women around them, and similarly, users in large cities would not believe there are 10 men or women around them. To obtain realistic values, m and w are drawn in the following way.

The experiment is implemented in two neighboring countries. Each country is divided into approximately 625 mi^2 grids.[5] For each grid g, I determine the population size M_g, which the number of men who have opened the app from within that grid in the two weeks prior the start of the experiment. Not all grids are selected to be in the experiment. Details on grid selection are in Section 4.2. When a treated user opens the app from a selected grid g, the treatment values m and w are drawn from a distribution centered around M_g. Specifically, both m and w deviate from M_g by factors, F^m and F^w, which are drawn from a V-shaped distribution between 0.75 and 1.25.[6] This variation in the treatment values is similar, if not smaller, than the natural variation in market thickness in this setting. Figure 16 in the Appendix displays how market thickness varies over time using historical data. Figure 4 displays the histogram of the draws of F^{ms}, where F^{ms} is the market size factor. Similarly, F^{cs} is the competition size factor.[7] In summary, the values displayed to the agent in the treatment message are correlated with the true number of agents in that grid, but the factor by which it deviates is randomized.

[5] Grids are formed by flooring each latitude and longitude to the nearest 0.75 (roughly a distance of 25 miles).

[6] The V-shaped distribution, as opposed to the uniform distribution, increases statistical power by increasing the variance of the treatment values.

[7] The market size for men is w, and competition size is w. Vice versa for women.

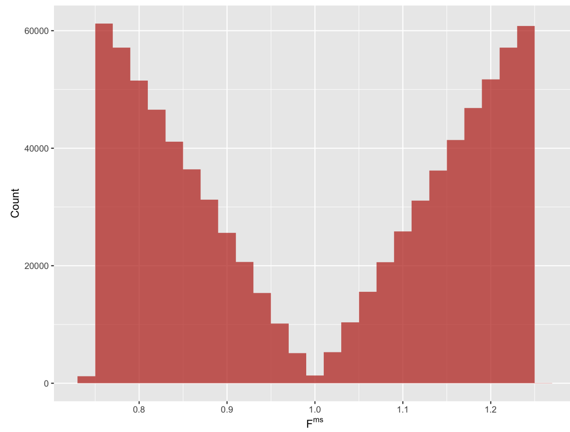

Figure 4: Histogram of F^{ms} across all sessions. Each observation is at the user-session level.

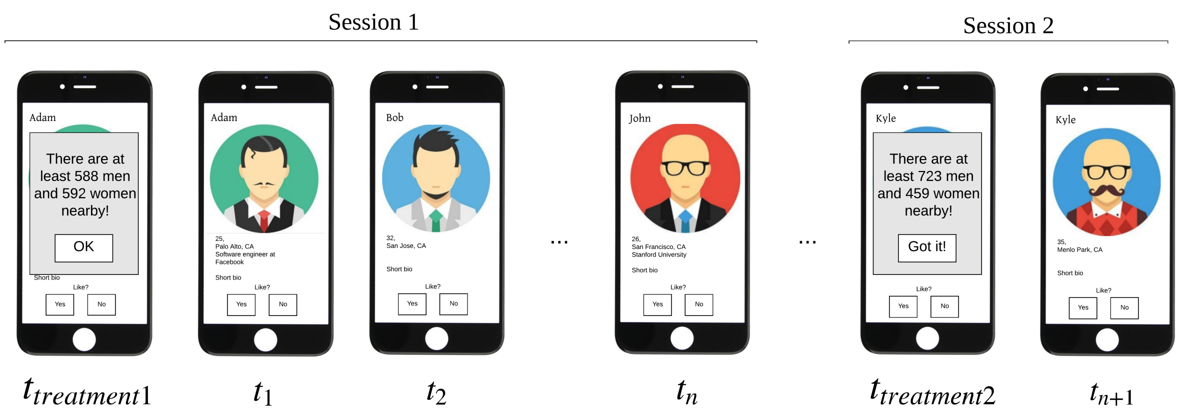

Figure 5: Example of how randomization occurs at the user-session level. The user is first exposed to the treatment at $t_{treatment1}$. She then views some profiles, and closes the app. If she opens the app at a later time and it has been at least 6 hours since $t_{treatment1}$, then he is exposed to the treatment again. The difference between $t_{treatment1}$ and $t_{treatment2}$ is always greater than or equal to 6 hours.

4.1.1 Session-level Randomization

There are two levels of randomization. The first is across users. Users in the treatment group can be exposed to the treatment, while users in the control group are not exposed. The second level of randomization is within the treated users at the session level. That is, treatment values m and w vary across users in the treatment group, and also within users at the session level.

Treated users are exposed to the pop-up message if (1) they open the app from within one of the selected grids, and (2) it has been at least 6 hours since they have seen the pop-up. A new session starts if it has been at least 6 hours since the user was last exposed to the treatment. Each time the treatment is shown, the treatment values are re-randomized. Figure 5 shows how the

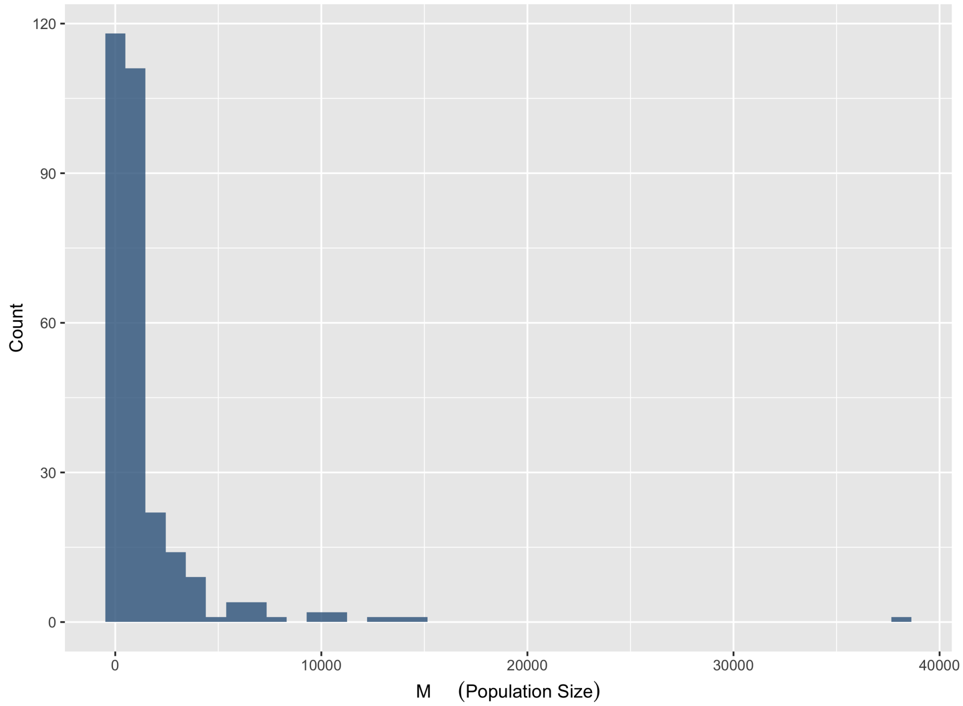

Figure 6: Histogram of the population size of each of the selected grids. This figure validates that the treatment values are indeed being drawn from a V-shaped distribution.

treatment values differ across sessions. For a treated user, at $t_{treatment1}$, he sees the treatment for the first time, with $m = 588$ and $w = 592$. After viewing some profiles, the user opens the app again at $t_{treatment2}$. If $t_{treatment2}$ is more than 6 hours after $t_{treatment1}$, the user is then shown the pop-up message again with new values of m and w. Conditional on the user's location, draws of m and w are independent across users and across sessions.

4.2 Sample Selection

4.2.1 Locations

The experiment is run in 2 neighboring countries where this app is popular. The identities of these countries are kept anonymous. Not all grids in these countries are selected for the experiment. The criteria by which grids are selected are that the grid must have a population size of at least 200, and must not include a large city.[8] A total of 292 grids fit this criteria.

Figure 6 displays a histogram of the population sizes of the 292 selected grids. Most grids are relatively small, with a population size of less than 1,000. One grid contains a relatively

[8]Whether a grid contains a large city is determined by the firm.

large city, with a population size of 37,000. The advantage of implementing this experiment with large variation in population sizes is that I can better measure the heterogeneous effects of market thickness across different types of markets.

4.2.2 Users

The sample is selected from 225,680 active users who are seeking matches with members of the opposite sex. These are men and women who have opened the app within a month prior to the start of the experiment from one of the selected grids. I randomly select 90% into the treatment group, and 10% into the control group, resulting in 203,170 and 22,510 users, respectively. I select 90/10 instead of 50/50 to maximize the number of people who are exposed to the treatment.[9] Prior to running the experiment, power calculations indicated a large sample is necessary to precisely measure effects, so the 90/10 split helps increase the number of people who are exposed to the treatment.

If the user does not open the app during the span of the experiment or does not open the app from one of the selected grids, he is not exposed to the treatment. After running the experiment for 3 weeks, 84,589 users were exposed to the treatment. Figure 7 summarizes the user sample selection process.

5 Data

5.1 Data Summary

I conduct the remainder of the data description and analysis on data from the agent's first session only to avoid potential selection problems, similar to Sahni and Nair (2016). Selection bias may arise in the following way. Individuals who see a lower draw of the market size may become less selective and be more likely to find a date. However, the low quality types, who are the least likely to find a date, will come back to the app and start a second search session. Thus, the sample of users who are exposed to the treatment in the second session are no longer random; the treatment in the first session affects which users are exposed to the treatment in the second session. This would

[9] The treatment effects of interest are measured by comparisons between users who see different values of the treatment, rather than comparisons between users in the treatment vs control groups.

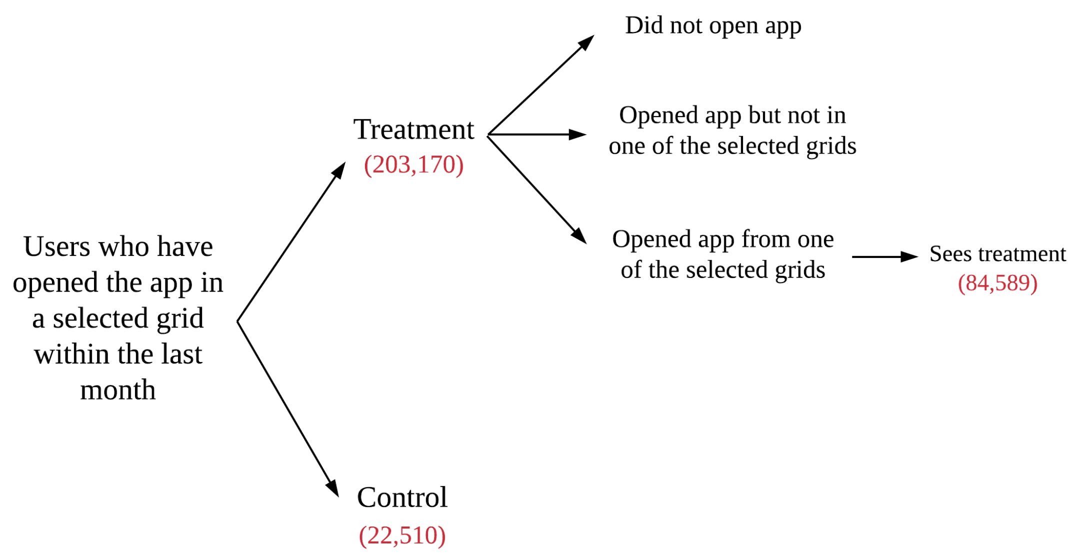

Figure 7: A summary of how users are selected into the experiment. Out of all the users who opened the app from one of the selected grids, 90% were selected into the treatment, and 10% into the control. Of the users in the treatment group, a user is exposed to the treatment if he opens the app from within one of the selected grids.

violate the stable unit treatment value assumption (Rubin 1974), where in this case, each unit is a user-session. To avoid these potential issues, data from the second session onwards is excluded from the analysis. After removing outliers and premium users from the data, there are 26,092 women and 40,647 men remaining.[10] Table 2 reports summary statistics for the number of profiles viewed, the proportion of profiles that were `liked` (`like` rate), and the number of matches made during the session. The `like` rate and number of matches are log transformed by an unreported base to maintain data confidentiality. The summary statistics demonstrate that there is considerable heterogeneity in search behavior both within and across genders. For example, on average, men view 35 profiles per session, but the median man views only 13 profiles. Women are also much more selective and get more matches than men.

The behavior also changes according to the "`like` limit". Figure 8 plots a histogram of the proportion of the `like` limit the user has remaining at the end of his session. For example, if the user has 100% of the `like` limit left at the end of the session, that means he did not `like` any other users during his session. The user hits the `like` limit when he has 0% left. The histogram shows that the `like` rate does bind for a subset of users. Moreover, while agents are not aware

[10]Premium users are removed from the data because they do not face the same dynamic forces as freemium users. A source of dynamics is the `like` limit; premium users do not have a `like` limit.

	Mean	SD	Median
Men (N = 40,647)			
Views	34.46	54.23	13.00
Like Rate	3.88	2.41	4.02
Matches	0.35	0.38	0.17
Women (N = 26,092)			
Views	44.25	78.74	11.00
Like Rate	0.69	1.14	0.26
Matches	0.49	0.54	0.17

Table 2: Descriptive statistics of agent actions in the first session. The `like` rate and number of matches are log-transformed by an unreported base to maintain confidentiality. On average, women search more, are more selective, and get more matches than men.

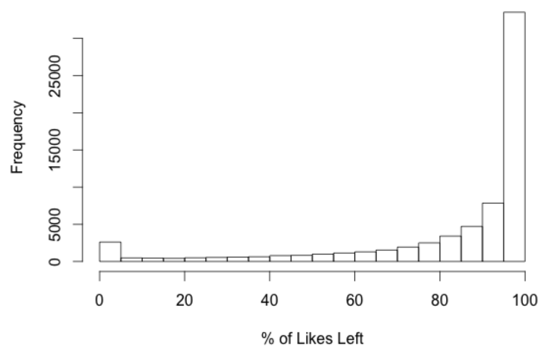

Figure 8: Histogram of the proportion of the `like` limit the user has remaining at the end of the session. Having 100% left indicates the user did not use any `likes` during the session.

of the exact number of `likes` they have left, the data suggests that agents are cognizant of how many `likes` they have left. Table 3 presents the results of a linear regression of whether a user i `likes` another user j on the percentage of `likes` he has left, and how many profiles he has already viewed. The first column is freemium users, and the second column is for premium users. The coefficient on the percentage of `likes` left for freemium users is significant and positive, meaning the user is more likely to `like` another profile when he has more `likes` left. HOwever, premium users do not exhibit this same behavior; there is no correlation between how many people they have already liked, and their propensity to like the next profile.

	Dependent variable:	
	$\mathbb{1}\{Like\}$	
% of Likes Remaining	0.072***	0.00000
	(0.005)	(0.00003)
Profiles Already Viewed	−0.00002***	−0.0001***
	(0.00000)	(0.00002)
User Type	Free	Paid
User FE	Y	Y
Observations	2,571,467	598,544
R^2	0.478	0.481
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: OLS of whether the user `likes` the other profile on the proportion of the `like` quota he has left, and how many profiles he has viewed during the session. The first column is for free users, and the second column is premium users only. Standard errors are clustered at the user level.

5.2 First Cut of Experimental Data

Before introducing the model, I first assess whether the treatment values shift behavior. The notation for the remainder of this section is the following. An agent i's market size is the number of agents of the opposite gender, and i's competition size is the number of agents of the same gender. M_i denotes the population size of the i's location when he was exposed to the treatment, and is measured in 10,000's. ms_i and cs_i are the market and competition size treatments, respectively, and F_i^{ms} is the market size factor, and F_i^{cs} the competition size factors. For example, if a male agent in a location with $M = 1000$ and sees the treatment "There are at least 900 men and 1200 women nearby", his market size treatment is 1200, competition size treatment is 900, market size factor F^{ms} is 1.2, and competition size factor F^{cs} is 0.9. To reiterate, F^{ms} and F^{cs} are between 0.75 and 1.25 and are truly random, while ms and cs are *random conditional on location.*

5.2.1 Selectivity

I first measure how selectivity changes with market thickness. How do individuals change their overall propensity to `like` another person, and does that change vary by the other individual's quality type? In other words, how does market size and competition size change the likelihood that the individual likes a high quality user compared to a low quality user? To measure the effect on selectivity, I run the following regression.

$$Like_{ij} = \alpha_\ell + \gamma_1 F_i^{ms} + \gamma_2(F_i^{ms} \times q_j) + \gamma_3 F_i^{cs} + \gamma_4(F_i^{cs} \times q_j) + \gamma_5 q_j + \gamma_6 X_i + \eta_{ij} \quad (2)$$

Each observation in this regression is one profile view, where i sees j's profile. q_j is the quality type of j's profile, measured in percentiles.[11] The effects of interest are the interaction terms of market size and competition size with q_j. To measure heterogeneous treatment effects across markets of different population sizes, I run this regression separately for agents in each tercile of population size.[12]

5.2.2 Search Intensity and Matches

To measure the average treatment effects, I run the following regression.

$$Views_i = \alpha_\ell + \beta_1 F_i^{ms} + \beta_2 F_i^{cs} + \beta_3(F_i^{ms} \times M_i) + \beta_4(F_i^{cs} \times M_i) + \beta_5 X_i + \epsilon_i \quad (3)$$

i is the individual who is exposed to to the treatment. $Views_i$ is the number of profiles that i views during the session. α_ℓ denotes location fixed effects. X_{it} are controls for individual characteristics. Specifically, I include controls for gender and i's quality type, in percentiles. An individual's quality type is measured by the ratio of users who have `liked` i's profile over the number of users who have seen i's profile. For instance, if $q_i = 1$, every individual who has seen i's profile has `liked` his profile. To obtain the percentile, i's quality type is compared to the quality type of all other users of the same gender. All quality measures are obtained from historical data, prior to the experiment. I also run the same regression to estimate the impact of the treatment values on $Matches_i$, the number of matches made during the session.

	Dependent variable:		
	$\mathbb{1}\{\text{Like}\}'$		
	(1)	(2)	(3)
F^{ms}	0.049	−0.015	−0.032***
	(0.043)	(0.037)	(0.011)
$F^{ms} : q_j$	−0.079	−0.017	0.078***
	(0.073)	(0.046)	(0.020)
F^{cs}	−0.088**	−0.053	0.030***
	(0.041)	(0.040)	(0.011)
$F^{cs} : q_j$	−0.004	0.068	−0.078***
	(0.072)	(0.061)	(0.020)
q_j	1.090***	0.868***	1.067***
	(0.100)	(0.079)	(0.029)
q_i	−0.491***	−0.525***	−0.604***
	(0.021)	(0.023)	(0.004)
Location FE	Y	Y	Y
M	Lower	Mid	Upper
Observations	843,915	998,496	712,899
R^2	0.302	0.285	0.135
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: OLS regression of Equation 2

5.3 Results

5.3.1 Selectivity

Table 4 presents the effect of market thickness on selectivity. The dependent variable is binary, but standardized for coefficient interpretability and data confidentiality[13] . Column (1) presents the results for users in markets with the bottom third tercile population size, (2) presents the middle tercile, and (3) the top tercile.[14] The interpretation of the coefficient is a 1 unit increase in x changes y by β standard deviations. The results show that market thickness has the biggest impact

[11] This is also measured from historical data.

[12] An alternative specification to measure heterogeneous effects across population size is to include an interaction between F^{ms}, q_j and M. I choose to estimate the specification in Equation 2 because 3-way interaction effects are more difficult to interpret.

[13] Standardization is $\frac{y-\bar{y}}{\sigma_y}$.

[14] This regression is estimated with OLS, rather than a logit, for easier interpretability.

	Dependent variable:	
	Views'	Matches'
	(1)	(2)
F^{ms}	−0.007	0.010
	(0.023)	(0.024)
$F^{ms}:M$	−0.006	−0.015*
	(0.007)	(0.008)
F^{cs}	−0.018	−0.039
	(0.026)	(0.028)
$F^{cs}:M$	0.012*	0.023***
	(0.007)	(0.009)
q_i	0.136***	0.358***
	(0.017)	(0.016)
Location FE	Y	Y
Observations	66,739	66,739
R^2	0.037	0.041
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5: OLS estimates from Equation 3. Standard errors clustered by location.

in large markets (with the exception of the significant effect of competition size in small markets).[15] In large markets, increasing market size beliefs by 50% causes 0.03 standard deviation decrease in the likelihood of `liking` another user with the 0 percentile quality, and 0.046 standard deviation more likely to `like` the highest quality user. In terms of percentages, this is equivalent to a 3% decrease in the likelihood of `liking` the lowest quality user, and a 2.8% increase in the likelihood of `liking` the highest quality user. The opposite is true for competition size. When an individual thinks he has 50% more competition, he becomes 2.3% (0.03 SD's) more likely to `like` the lowest quality user and 4.5% (0.038 SD's) less likely to `like` the highest quality user.

5.3.2 Search Intensity and Matches

Table 5 displays the OLS estimates of Equation 3. The dependent variable in column (1) is the standardized number of profile views. (2) is the standardized number of matches.

There is no significant effect of market thickness on search intensity. The effect of $F^m s$ on search intensity is negative but not statistically significant. On average, a 50% increase in competition size increases the profile views by 1% (0.006 standard deviations).

As shown in Column (2), for the average market ($M = 11,000$), increasing an individual's beliefs about market size by 50% decreases matches by 2% (0.008 standard deviations), and increasing beliefs about competition size by 50% results increases matches by 3% (0.012 standard deviations). These individual effects are significant but small in magnitude, as matches are relatively rare in the data as compared to profile views and `likes`.

5.4 Discussion

The takeaway from this experiment is that individuals respond to beliefs about market thickness in a way that is consistent with the adjustment of search and selectivity. The platform is able to change who an individual proposes a match with through information about the number of men and women nearby. When an individual believes that he has a larger market size, he becomes more selective and as a result, gets fewer matches. Conversely, when he believes he has more competition, he becomes less selective and gets more matches. The absolute magnitudes of these effects are small, but I believe these effects are relatively large and surprising, given the strong role that inherent preferences play in this setting. In addition, q, the quality measure may be noisy, resulting in attenuation bias, especially in Table 4.

While the experiment is able to identify a causal effect and show evidence of the mechanism, it is inadequate to simulate counterfactual policies. The experimental results show the effect of *beliefs* about market thickness on selectivity and matching. The next step is to analyze its implications for matching with the market thickness actually increases or when platform design features change. The following section describes in more detail the role of the model in counterfactual analysis.

[15] This may be because a 50% change in market thickness is greater in terms of the absolute number of users than a 50% increase in a smaller market.

6 Model

6.1 Motivation

The goal of this model is to guide platform design through the analysis of counterfactuals, and to organize the various empirical results through a set of parsimonious parameters that can explain the behavior. While the platform can answer some policy questions through experimentation, many relevant counterfactuals may be too costly, or even impossible to test. The experimental results are not enough to estimate matching outcomes under different counterfactuals for two reasons. First, interpreting individual effects of market thickness on matching as a whole is not straightforward. In particular, if market size increases for one side of the market, by definition, competition increases for the other side. Thus, the direction of the overall impact of changing market thickness is not clear due to the different individual effects of market and competition sizes. Second, matching is the result of a Bayesian Nash equilibrium. The idea that each agent's behavior depends on his beliefs about other agents' behavior is inherent to matching markets. Matching is a two-sided decision, and an agent does not know whether the other agent is willing to match. Therefore, he forms beliefs about j's actions and behaves optimally according to these beliefs, which is the equilibrium of the game. Thus, the effects of a policy implementation must be interpreted as the result of an equilibrium of a dating game of imperfect information between men and women.

6.2 Model Details

This paper builds a model of search and selectivity in order to simulate matching outcomes. In other words, matching outcomes are treated as a statistical process determined by the agent's joint decision for how much to search and which agents to `like`. Modeling matches in this way allows me to pool all the actions an agent can take in a cohesive way. The structural model also allows me to incorporate a current policy that is a driver of agent behavior and a source of dynamics: the `like` limit. The agent's actions in the current time period affects how many `likes` he has left in the next time period, and Table 3 provides evidence that agents behave accordingly. Not only does this policy influence agent behavior, but the platform also uses this policy as a source of monetization. Agents can pay to subscribe to the premium version of this app, which does not have a `like` limit. Motivated by the fact that the `like` limit adds an additional source of dynamics that drives selectivity and is an important policy for monetization, the `like` limit is an integral aspect of this model for counterfactual analysis.

The foundation of this model is built on sequential search and is extended to allow for two-sided matching. The exogenous variation in market thickness in the experiment is introduced at the search session level, so I model an agent's search for a single session as well. That is, I model one episode of search for each agent, and I assume that agents are not forward-looking across search episodes. This mirrors the analysis strategy in the descriptive section. In each time period t in the session, the agent can view one profile. In a session with T time periods, the agent can view up to T profiles. The agent's objective is to find another agent to go on a date with and to maximize the utility from that date (date utility), subject to costs incurred from search.

In the following paragraphs, I first an overview of the model by describing how the experiment changes beliefs, and the timing of the agents' actions. I then discuss the agent's states, actions, and utilities in more technical terms. Lastly, I explain how market thickness enters the model and discuss the equilibrium in more detail.

6.3 Timing of Agent Actions

6.3.1 Belief Updation

The parameters of the model are identified based on the experimental variation in *beliefs* about the number of men and women in the market. I first describe how agents update their beliefs as a result of the treatment before explaining how the agent acts based on these beliefs.

Prior to the experiment, at the beginning of each search session, an agent has beliefs about his market thickness, denoted by $\tilde{m}_\tau$ and $\tilde{w}_\tau$, which are beliefs about the number of men and women, respectively, at session τ. For the remainder of the paper, tilde's denote beliefs. Given $\tilde{m}_\tau$ and $\tilde{w}_\tau$, he also forms beliefs about $\tilde{f}(q; \tilde{m}_\tau, \tilde{w}_\tau)$, the quality types of profiles that the matching algorithm will present; and $\tilde{\pi}^{like}(q; \tilde{m}_\tau, \tilde{w}_\tau)$, the probability that other agents of type q will `like` him.

At session $\tau' > \tau$, the experiment informs the agent that his market thickness is $m^*_{\tau'}$, and $w^*_{\tau'}$. I make the following assumption.

Assumption 1. *Agents update their beliefs to the treatment values after being exposed to the*

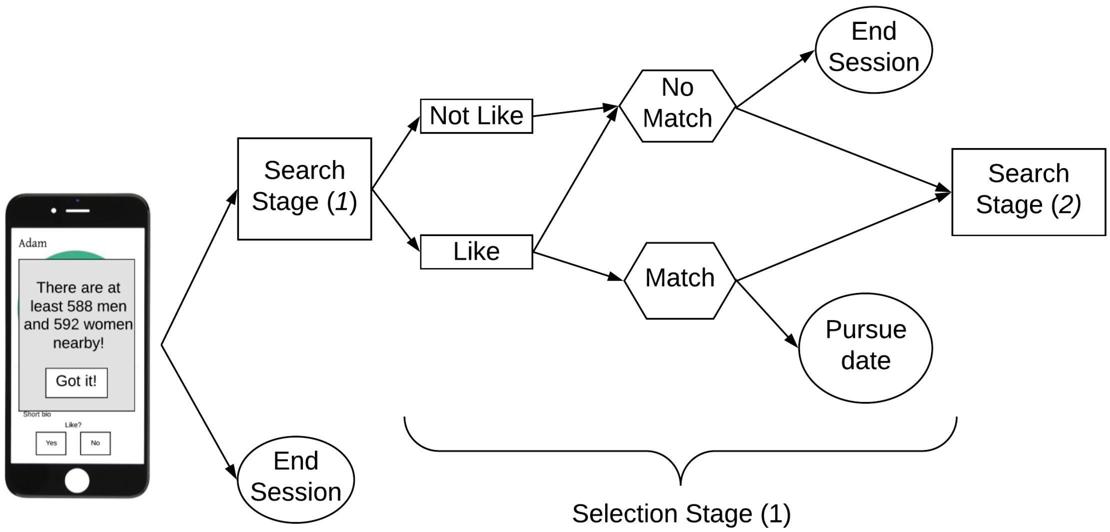

Figure 9: This figure shows the actions the agent can take after seeing the treatment. After being exposed to the treatment, he can either enter the search stage or end the session. If he enters the search stage, he evaluates the profile and then enters the selection stage. The selection stage can result in the following possible actions: (1) the agent matches and pursues a date with the other agent, (2) the agent matches and decides to continue searching in the next time period, (3) no match is formed, and the agent continues to the search stage in the second time period, or (4) no match is formed, and the agent ends the session.

treatment.

This assumption implies the agent completely believes the treatment values. This assumption is plausible due to how the treatment values are assigned. The treatment value for the number of men randomized such that it is centered around the true number of men in the market. On the other hand, the treatment value for the number of women is not centered around the true number of women in the market, so this assumption is more likely to be violated for the beliefs about the number of women.

The agent then updates his beliefs about the distribution of quality to $\tilde{f}(q; \tilde{m}_{\tau'}, \tilde{w}_{\tau'})$, and the others' `like` probability to $\tilde{\pi}^{like}(q; m^*_{\tau'}, w^*_{\tau'})$.

6.3.2 Actions during the Session

Given new beliefs about the state of his market, he then begins a search session. Figure 9 summarizes the timing of the steps in the model starting from when the agent is exposed to the treatment. i first observes his market thickness, and updates his beliefs in the manner described in the previous section. He then decides whether to not search, or to enter the search stage. The rectangles represent the actions in the model. The circles depict endpoints in the search session; the session ends if i pursues a date or if he decides to end the session without pursuing a date. The hexagons represent uncertainty from i's perspective. If he `likes` j, he is uncertain about whether a match will form because he does not know whether j `likes` him back.

There are two stages within each time period: the search stage and then the selection stage. In the search stage, the agent i views an agent j's profile. In doing so, he incurs a search cost of viewing the profile c^v and then continues to the selection stage. In the selection stage, he chooses to `like` or not `like` the profile. If he `likes` the profile, a match may occur. A match forms if i `likes` j and j also `likes` i. If i and j match, i screens j's profile at a cost c^m. This may involve looking more closely at j's profile or exchanging messages. After screening, i then decides whether to pursue a date with j. If he does not pursue a date with j, then he enters the search stage again in time $t+1$. However, if either i does not like j or j does not `like` i, no match is formed. The agent can then decide to end the search session without pursuing a date, or continue to the search stage in $t+1$.

i receives the date utility from j if and only if i and j mutually pursue a date with each other. At the time i decides to pursue a date with j, he does not know whether j pursues a date with him. Thus, if he chooses to pursue a date with j, he receives the expected date utility ρ_{ij}.

6.4 Market Thickness

In a centralized market, an agent's belief about how likely he is to find a date depends on the ratio of men to women. For instance, a male agent may believe that he has a better chance of being assigned a date if the ratio of men to women decreases. Allowing agents to search for a date complicates this process, as an agent's search and selectivity decisions will be affected by this belief. Consider a simple search model where an agent `likes` a profile if the expected date utility is greater than the expected value of continuing search. Intuitively, if the market to competition size ratio is high, the agent believes he has a good chance of finding a date. As a result, he may be less likely to `like` the current profile because (1) `likes` are costly, and (2) he believes he should be able to end up with a better date if he continues searching.

To link this intuition to the model, market thickness enters through its effect on an agent's value of continuing search, and the probability that another agent sees i's profile. Also, due to the nature of the game, market thickness has indirect and direct effects. I refer to indirect effects as effects that change i's behavior through changing i's beliefs about other agents' actions. For instance, if i has more potential matches, that means j has more competitors. Thus, i may believe that j may be more likely to `like` i's profile. Conversely, direct effects change i's utility, even if beliefs about how other agents' behave remained constant. In the following section, I describe the direct effects of market and competition size.

6.4.1 Market Size

Market size can enter the model through two ways: quality and quantity. The most obvious way is through quantity. When there are more agents in the market, the agent has more search opportunities. While this aspect of market size may be relevant in smaller markets, in the markets in this experiment, the quantity of agents is not binding. That is, the market size is so much greater than the agent's search intensity during a session than running out of search opportunities is not a concern. Therefore, I model market size through its effect on the agent's belief about the type of agent he will see in the next search opportunity.

There are a multitude of reasons why market size would affect beliefs on the quality type of agents in the next time period. First, when the market size increases, new agents are joining the platform, and those new agents may be of a different type than existing agents. It is plausible that the incremental users may be different from the ones who have already on the platform. Second, the platform's matching algorithm may augment the effect of market size. When there are more agents on the platform, there are also more high quality agents. If the agent believes that the matching algorithm sorts the order in which profile are shown by quality, when market size increases, the quality of the next agent shown should be on average higher than if the market size had decreased. Third, psychology literature shows evidence that when individuals have more choice, they have greater expectations about the ability to find a match that better aligns with their preferences (Diehl and Poynor 2010). That is, when there are more alternatives, individuals believe they will find a better match.

The data cannot distinguish between these mechanisms, but the overall effects would manifest in similar ways: market size affects beliefs about the quality of agents shown in the next time period. I cannot measure how much of the overall effect comes from each mechanism. Therefore, I measure the aggregate effect of market size and am agnostic about how much each mechanism contributes to the overall effect. I model the effect with the following specification.

$$q_{it} \sim TN(\tilde{\mu}_i, \tilde{\sigma}_i^2)$$
$$\tilde{\mu}_i = \hat{\mu}_i + \delta_1 F_i^{ms} + \delta_2 F_i^{ms} \times M_i$$

TN denotes a truncated normal distribution, bounded between 0 and 1, with mean $\tilde{\mu}_i$ and variance σ_i^2. $\hat{\mu}_i$ is the agent's prior belief about the mean quality of the distribution of q, which can be estimated by the true quality types of profiles that i sees prior to the treatment. Post treatment, the mean is shifted by F_i^{ms}. The interaction term δ_2 captures heterogeneity in the effect of market size across markets of different population sizes.

6.4.2 Competition Size

When there is more competition, the chance that another agent has seen a given agent's profile decreases. For example, in the labor market, when an unemployed worker has more competition, it becomes less likely the firm sees his resume. In this model, for each profile that he sees, when the agent believes that when there is more competition, it is less likely that the other agent will match with him because the other agent is less likely to see his profile.

As described previously, if i `likes` j, i and j match only if j sees i's profile and j `likes` i's profile. Thus, i's belief about the probability that they match is specified as the following.

$$\begin{aligned} \tilde{\pi}_{ij}^{m} &= \tilde{\pi}_{ji}^{like} \tilde{\pi}_{ji}^{see}(cs) \\ &= \tilde{\pi}_{ji}^{like} \frac{\bar{s}_i}{cs_i} \end{aligned} \tag{4}$$

$\bar{s}_i$ measures the extent that competition cs affects i's belief that an agent in his market will see his profile. It can be interpreted as an approximation of i's belief about the combination of likelihood that the platform will serve i's profile to j, which depends both on j's search intensity and the platform's matching algorithm. If i believes that j views many profiles, competition has a small effect on whether j sees i's profile. If $\bar{s}_i$ is much greater than cs, competition does not have a direct effect i's belief on matching because it does not alter whether j sees i's profile.

6.5 Model Assumptions

Before going into more technical description of the model, I first lay out the modeling assumptions.

Assumption 2. *An agent gets utility from a match only if they go on a date.*

This is a strong assumption, as it is plausible that agents go on the platform just to browse or chat online.

Assumption 3. *The expected utility of ending the search session without pursuing a date is 0.*

In line with discrete choice models, the outside option is normalized to have 0 utility. Future iterations of this model may include allowing for the utility from the outside option to vary with matches made in previous sessions.

Assumption 4. *At time t, the agent does not consider pursuing a date with matches formed at $t' < t$.*

This is, again, a strong assumption. In reality, the agent's search process may be more simultaneous rather than sequential. During the search session, he may accrue a set of matches. Once the agent has enough matches, he may decide to stop search and screen the matches all at once. However, in the data, of the users who get at least one match, the majority of users get a single match, which supports this assumption.

Assumption 5. *Conditional on i, and within a session, i believes the draws of q are independent across t.*

The quality of profiles that are shown to i are correlated with q_i, as shown by Table 10 in the Appendix. In other words, users are more likely to see profiles of other users similar in quality For example, high quality type agents are more likely to see other high quality type agents, which implies quality should be weakly decreasing as agents search. If the agent viewed every profile in his market in one session, the average quality of agents at the beginning of the session should be greater than those of agents at the end of his session. However, the rate that quality declines across searches depends on how precisely the algorithm sorts. If the algorithm presents profiles in order of strictly decreasing quality, then this assumption would not be valid. I validate in the data that profiles are not presented in strictly decreasing quality. In addition, conditional on searching, the median number of searches per session is 29, so most agents do not search enough within a session to see a decline in average quality. I empirically observe a lot of variance in the order in which profiles are shown. While there is a high correlation between i's quality type and the average quality type of agents shown to j, there is no statistically significant correlation between q_t and t within a search session. Evidence for this is presented in Table 10 in the Appendix.

6.6 Actions and States

There are four states in this model, $x_{it} = \{L_{it}, q_{it}, ms_i, cs_i\}$

1. $L_{it} \in \mathbb{Z}_0^{\bar{L}}$: the `like` limit, which is an integer between 0 and $\bar{L}$
2. $q_{it} \in [0, 1]$: quality type of the agent whose profile is served to agent i
3. ms_i: the agent's market size at the start of the session
4. cs_i: the agent's competition size at the start of the session

At the beginning of time t, agent i knows his state L_{it}, which is the number of `likes` he has left. An agent is forward looking in how many `likes` he has left. If he has very few `likes` left, he may become more selective in who he `likes` in the current period to ensure that he can continue searching. Thus, L_{it} is the only "endogenous" state, where the actions at t affect $L_{i,t+1}$.

The set of actions an agent can take depends on the state L. If $L_{it} = 1$, and the agent `likes` the profile at t, i is not able to search in $t+1$. Conditional on entering the search stage, the agent's states are $\{L_{it}, q_{it}\}$, and the set of actions in the selection stage is $a_{it}^{selection} = \{l, nl\}$, where l is `like` and nl is not `like`.

The state transitions are the following. Every time the agent `likes` another agent, L decreases by 1. If $L_{it} = 1$ and $a_{it} = nl$, then the agent's search session ends at t.

$$L_{i,t+1} = \begin{cases} L_{it} & a_{it} = nl \\ L_{it} - 1 & a_{it} = l \end{cases}$$

The state transition for q_{it} is the following.

$$q_{i,t+1} \sim N(\mu_i, \sigma_i^2) \tag{5}$$

μ_i and σ_i^2 describe the distribution q of profiles that i believes the platform will serve to him.

6.7 Current Period Utilities

Before the agent decides whether to end the session or continue searching, he observes idiosyncratic, choice-specific shocks ϵ_{it}^{ss} and ϵ_{it}^{s}. If he chooses to stop searching, he receives the following utility.

$$u^{ss} = \epsilon_{it}^{ss} \tag{6}$$

Search Stage

In the search stage t, the agent views a profile j and observes and forms beliefs about the following.

1. q_j: the quality type of j
2. $\rho_i(q_j)$: the expected utility that i receives from pursuing a date with j
3. $\tilde{\pi}_{ij}^{m}$: i's belief that i and j will match, conditional on i `liking` j
4. π_{ij}^{d}: the probability that i will pursue a date with j, after matching and learning the true expected date utility

$\rho_i(q_j)$, the expected date utility, captures i's belief on whether the date will be realized. Formally,

$$\rho_i(q_j) = \pi_{ji}^{d}\tilde{\rho}_{ij} \tag{7}$$

where $\tilde{\rho_{ij}}$ is the utility that i receives from a realized date with j, and π_{ji}^{d} is the probability that j also pursues a date with i. However, I cannot observe π_{ji}^{d} the data, so I am unable to separate π_{ji}^{d} from $\tilde{\rho}_{ij}$.

After observing viewing the profile, i incurs a search cost c^v. Thus, the current period utility for searching is the following.

$$u^{s} = -c^{v} + \epsilon_{it}^{s} \tag{8}$$

For the remainder of the paper, I denote $\rho_i(q_j)$ by ρ_{ij} for ease of exposition.

Selection Stage

In the selection stage, the agent decides whether to `like` or not `like` j. The utility for `liking` j is the following.

$$u_{it}^{l}(q_j) = \alpha_i^l + \tilde{\pi}_{ij}^m(-c^m + \pi_{ij}^d E[\rho_{ij} + \epsilon_{ij}^d]) + \epsilon_{ijt}^l \tag{9}$$

α_i^l captures heterogeneity in an individual's propensity to `like` other agents. If i `likes` j, i believes there is a probability $\tilde{\pi}_{ij}^m$ that they match.

The second part of the right-hand side of Equation 9 is the utility that i receives if they match. If i and j match, i screens j's profile. This may involve having a conversation with j or looking at j's profile more closely. Doing so incurs a screening cost c^m. During screening, i forms a belief about the likelihood that j pursues a date with i. He then updates his expected date utility to $\rho_{ij} + \epsilon_{ij}^d$, where ϵ_{ij}^d is a shock that is observed by i but unobserved by the econometrician. i then decides whether to pursue a date with j by comparing the expected date utility and utility shock to the value of continuing search in the next time period. Specifically, i pursues a date with j if

$$\Pr\left(\rho_{ij} + \epsilon_{ij}^d > V_{i,t+1}^s + \epsilon_{i,t+1}^s\right) \tag{10}$$

At the time that i decides to `like` j, he does not observe ϵ_{ij}^d. Hence the expected value of the expected date utility over ϵ_{ij}^d in Equation 9.

ϵ_{ijt}^l shock represents a shock that is observed by i before the screening stage. Examples of this shock are the contents of j's profile, such as pictures or the bio, that influence the propensity of i to `like` j. The implicit assumption is that these shocks are independent of i's beliefs about the likelihood of matching and j pursuing a date.

If i does not `like` j, he receives an idiosyncratic shock.

$$u_{it}^{nl} = \epsilon_{ijt}^{nl} \tag{11}$$

Figure 10 provides a detailed summary of the steps of the model.[16] Specifically, it shows during each step, what actions the agent takes and the utilities received from those actions.

[16] Figure 10 is located at the end of the document.

6.8 Value Functions

Each agent i maximizes the following optimization problem.

$$\max_{\vec{a}=(a_0,a_1,a_2...)} E\big[\sum_{t=0}^{T} u_i^a(x_{it})\big]$$

i chooses an action a during each time period to maximize his overall expected utility. The value functions for stopping search, search, and not `like` are below. i subscripts are dropped for ease of exposition.

$$V_t^s(L) = -c^v + \int_q \max\left(V_t^l(L,q) + \epsilon_{j,t}^l, V_t^{nl}(L)) + \epsilon_{j,t}^{nl}\right) dF(q;ms) \tag{12}$$

$$V_t^{nl}(L) = E[\max(V_{t+1}^s(L) + \epsilon_{t+1}^s, \epsilon_{t+1}^{ss})] \tag{13}$$

Equation 12 is the value function for searching. If i searches, he incurs a search cost c^v. The continuation value is the expected maximum utility from the selection stage, where i either `likes` or does not `like` the agent shown at t. However, before deciding to search, he does not know what the quality type of profile that will be shown, so he forms his expectation based on his belief about the distribution of q, which is a function of his market size ms.

Equation 13 depicts the value function for not `liking`. If he does not like, his utility is the expected maximum utility from searching in the next time period, or ending the search session.

$$\begin{aligned} V_{it}^l(q,L) =& \alpha_i^l + \tilde{\pi_j}^{like}\tilde{\pi_j}^{see}(cs)(\pi_i^d\rho - c^m) + \\ & (1-\tilde{\pi_j}^{like}\tilde{\pi_j}^{see}(cs)\pi_i^d)E[\max(V_{i,t+1}^s(L-1) + \epsilon_{i,t+1}^s, \epsilon_{i,t+1}^{ss})] \end{aligned} \tag{14}$$

Equation 14 is the value function for `liking` the profile of type q. As described in the previous section, the first line in this equation is the current period utility that an agent receives. $(1 - \pi_j^{like}\pi_j^{see}(cs)\pi_i^d)$ is the probability that i does not pursue a date with j. If i does not pursue date, his continuation value is the expected maximum utility of stopping search, or entering the search stage in $t+1$.

I parameterize ρ as the following, where λ_i represents the extent that the quality q_j affects the expected date utility.

$$\rho_{ij} = \lambda_{1i} q_j$$

6.9 Beliefs about Market Thickness in Equilibrium

This section demonstrates the indirect effects of market thickness. Clearly, an agent's behavior depends on his beliefs about other agents' behavior. In particular, an agent's decision to `like` another agent depends on his beliefs about whether the other agent will `like` him back. I illustrate the equilibrium concept with the following system of equations. Each agent on this platform has imperfect information about how other agents will behave. Therefore, they form beliefs about other agents' behavior. In particular, i's decision to `like` agent j, conditional on seeing j's profile, is a function of i's belief about j will `like` i, $(\tilde{Like}_{ji})$, and i's expected utility from continuing to search. Similarly, j's decision to `like` i, conditional on seeing i's profile, depends on $\tilde{Like}_{ij}$, and her value of continuing search. If i and j are symmetric, their actions can be written as the following.

$$Like_{ij} = g\big(\tilde{Like}_{ji}, V^s_{i,t+1}\big) \tag{15}$$

$$Like_{ji} = g\big(\tilde{Like}_{ij}, V^s_{j,t+1}\big) \tag{16}$$

As described in the previous section, market and competition have direct effects on the value of continuing search, and the likelihood that another agent sees i's profile. Thus, $V^s_{i,t+1}$ is a function of the market and competition size. Equations 15 and 16 can be rewritten as the following.

$$Like_{ij} = g\big(\tilde{Like}_{ji}(ms_j, cs_j), V^s_{i,t+1}(ms_i, cs_i)\big) \tag{17}$$

$$Like_{ji} = g\big(\tilde{Like}_{ij}(ms_i, cs_i), V^s_{j,t+1}(ms_j, cs_j)\big) \tag{18}$$

This system of equations clearly demonstrates the equilibrium concept of decentralized matching markets. Because ms_i and cs_i affect i's decision to `like` j, j's decision to `like` i is not only a direct function of ms_j and cs_j, but also ms_i and cs_i. Since i does not know ρ_{ji}, j's date utility from going on a date with i, and i does not know j's actions, this platform can be modeled as a Bayesian game with incomplete and imperfect information. In this game, each agent has beliefs over the actions of other agents, given their quality. The equilibrium consists of a strategy profile where an agent with quality q_i has an action that maximizes his expected payoff for each quality profile that he sees. Section 11.3.1 in the Appendix goes into more detail on the characterization of this game.

As the econometrician, each agent's actions that I observe are the optimal response given their beliefs about the actions of other agents. Since market thickness can change beliefs about the actions of other agents', the estimation method must take these indirect effects in the equilibrium into account.

7 Estimation

7.1 Overview

Estimating the equilibrium of a dynamic game is not trivial, especially when there are many agents. Two-step methods, such as Hotz and Miller (1993) and Bajari, Benkard, and Levin (2007), drastically reduce the computational burden of making inference on parameters by avoiding equilibrium estimation. The main idea of these estimators to estimate the equilibrium beliefs in the first stage from the observed data.

Before going into details on the estimation procedure, I provide intuition on how I apply the two-step estimator to this paper. Given an agent's beliefs about his market and competition size, he also has beliefs about how other agents in his market behave, which are conditional on his own market thickness. That is, when a man thinks there are more women in his market, he also knows that the women in his market have more competition. Thus, he updates his beliefs about the likelihood that a woman will `like` him, and optimizes his behavior given these beliefs. But what are these beliefs? Given the assumption about rational beliefs, the econometrician can approximate the beliefs with the observed data. The man's beliefs about how a woman behaves in a market with m men and w women are the same as a woman's actual actions in that market.

A challenge arises from the fact that the treated users beliefs are different from the non-treated users' beliefs. To elaborate, the experiment changes a treated agent's beliefs about his market thickness to m^* and w^*, so he believes other agents are also in a market with m^* men and w^* women and behave accordingly. However, in reality, the other agents in his market behave based on the true market thickness, which is not equal to m^* and w^*. Thus, a treated agent's beliefs about others' actions cannot be approximated with the other agent's actions.

To overcome this estimation challenge, I estimate beliefs using historical data where I can observe agents in markets where the true market thickness is equal to the experimental market thickness. That is, for an agent with market thickness beliefs m^* and w^*, I approximate his belief about other agents' actions with observed actions from agents in markets with m^* men and w^* women. An added advantage of using historical data is the volume of data; this large amount of data allows me to estimate the first stage as flexibly as possible. However, to leverage this data set, I must make the assumption that the prior to the experiment, agent's beliefs about his market thickness are equal to his true market thickness.

Assumption 6. *Prior to the experiment, the agent has rational beliefs about how many men and women are in his market.*

In line with two-step estimation literature, I also make the assumptions that agents have rational beliefs about other agents' actions, and the data, both historical and post-treatment, is generated from the same equilibrium profile (Bajari, Benkard, and Levin 2007).

Another caveat of the pre-experimental data is that the variation in market thickness is not exogenous. However, I do not think this is a major concern due how individuals make inference about other's actions. It seems reasonable that an individual does not update his beliefs from $\tilde{\pi}^{like}(q|\tilde{m}, \tilde{w})$ to $\tilde{\pi}^{like}(q|m^*, w^*)$ based on the *causal* effect of market thickness. They may update their beliefs about what they know from past experience or from other markets.[17]

7.2 Identification

There exists significant hetereogeneity in this data, as evidenced by the large standard deviations in Table 2, so I estimate parameters at the individual level. For each agent i, the parameters to be estimated are $\theta_i = [\delta_{1i}, \delta_{2i}, c_i^v, c_i^m, \bar{s}_i, \lambda_i, \alpha_i^l]$. δ_{1i} and δ_{2_i} are identified by the randomization introduced by the experiment. I leverage the exogenous variation generated by the experiment to estimate the parameters. For example, without the experimental variation, I would not be able to

[17] Figure 17 in the Appendix plots the difference between observed actions in pre-experimental data vs post-experimental data.

identify whether an individual's propensity to `like` other agents is due to an inherent characteristic (α_i^l), or a causal effect of his market size.

δ_{i1} captures how changes in market size correlates with the agent's belief about μ_q. c^v is identified by how much an agent searches. To illustrate, if two agents see the same treatment values, the difference in how much they search would inform the search cost parameter. c^m is identified by the frequency at which an agent `likes` another agent and by the quality types of the agents that are liked. When the screening cost increases, agents would become more likely to `like` agents with higher expected date utilities. Intuitively, λ is identified by the extent an agent likes higher quality agents over lower quality agents. If high quality agents are much more likely to be `liked` than low quality agents, I would expected λ to be positive and large. Lastly, α_i^l is identified by individual-level differences in the probability of `liking` that exist after accounting for the other parameters. To further ensure each parameter can be identified, I estimated the model on simulated data and was able to recover the parameters.

7.3 Two-Step Estimation

7.3.1 First Step

The goal of the first step is to estimate an agent's beliefs about other agent's behavior, given his treatment values. I do so by using pre-experimental data from individuals in both the treatment and control group. The relevant beliefs in the second stage is the likelihood that an agent of quality q `likes` i, given values of market thickness. While the number of likes a person has left is an endogenous state variable and affects a person's decision to like, I assume that the i's beliefs about j's behavior is not explicitly dependent on their L state. Because there are so many agents in the market, and L is private information, i optimizes his actions based on the beliefs about the average long-run behavior of other agents over the distribution of other agents' L. This concept has been referred to as a *stationary equilibrium* (Hopenhayn 1992).

Let $\hat{\pi}_m^{like}(q_i, q_j, m_j, c_j)$ denote the belief that a man, with quality q_i, has about the likelihood a woman with quality q_j will `like` him, given her market size ms_j and competition size cs_j. Likewise, $\hat{\pi}_w^{like}(q_i, q_j, m_j, c_j)$ is a woman's belief that a man of type q_j will `like` her. I estimate $\hat{\pi}_m^{like}(q_i, q_j, m_j, c_j)$ in the following way.

1. Divide quality types for men, women and number of men and women into bins.

   (a) $q^w = \{q_1^w, ..q_N^w\}$, $q^m = \{q_1^m, ...q_N^m\}, m = \{m_1, ...m_{N'}\}, w = \{w_1, ..., w_{N'}\}$

2. For each grid point n in q^m, run the following logit regression for all men i such that $q_{n-1}^m \leq q_i < q_n^m$. This gives the probability that a woman of type q_j in a location l with m_l men and w_l women `likes` i.

$$Like_{jil} = \beta_1 + \beta_2 q_j + \beta_3 q_j^2 + \beta_4 m_l + \beta_5 m_l^2 + \beta_6 w_l + \beta_7 w_l^2 + \eta_{jil}$$

   (a) Predict for all grid points: $\hat{\pi}_m^{like}(q_n^m, q^w, m, w) = L\hat{i}ke(q^w, m, w)$

This results in a 4-dimensional matrix $\hat{\pi}_m^{like}(q^m, q^w, m, w)$, which is the probability that a woman of type q^w `likes` a man of type q^m in a market with m men and w women. The process is similar for estimating women's beliefs.

7.3.2 Second Step

I estimate the parameters in the second step for men and women separately. The effect of the market size factor F^{ms} is specified as follows. Prior to the treatment, the agent's belief about q_{t+1} is that is drawn *iid* from a truncated normal distribution between 0 and 1, with mean $\hat{\mu}_i$ and standard deviation $\hat{\sigma}_i^2$. After being exposed to the market size m_i, his belief about q_{t+1} shifts.

$$\begin{aligned} q_{t+1} &\sim TN(\mu_i, \sigma^2) \\ \mu_i &= \frac{\exp(\tilde{\mu}_i + \delta_1 F_i^{ms} + \delta_2 F_i^{ms} M_i)}{1 + \exp(\tilde{\mu}_i + \delta_1 F_i^{ms} + \delta_2 F_i^{ms} M_i)} \\ \tilde{\mu}_i &= \log(\frac{\hat{\mu}_i}{1 + \hat{\mu}_i}) \end{aligned}$$

μ_i is transformed such that it is between 0 and 1. $\tilde{\mu}_i$ is specified such that if $\delta_1 = 0$ and $\delta_2 = 0$, then $\mu_i = \hat{\mu}_i$. In other words, δ_1 and δ_2 describe the extent the change in market size beliefs shifts μ_i from $\hat{\mu}_i$. σ_i^2 is estimated as the observed standard deviation of quality types of agents of the opposite gender. That is, if i is a man, then $\sigma_i^2 = \hat{\sigma}_w^2$, which is the standard deviation of q for all women in the treatment and control groups. The specifications of the remaining parameters are straightforward.

Likelihood Function

Given the estimated agent beliefs from the first step, I estimate the parameters via maximum likelihood. The value functions are estimated as a finite horizon problem with $T = 500$ with no time discounting across periods within a session. I select $T = 500$ because it is much greater than the observed maximum searches per session. Because the errors are assumed to be iid EV Type 1, the probability of taking each action given states at t can be simplified to the following.

$$\Pr(s_{it}, \ell_{it}) = \frac{\exp(V^s(L_{it}))}{1 + \exp(V^s(L_{it}))} \times \frac{\exp(V^{\ell}(L_{it}, q_{it}))}{\exp(V^{\ell}(L_{it}, q_{it})) + \exp(V^{n\ell}(L_{it}))} \tag{19}$$

$$\Pr(s_{it}, n\ell_{it}) = \frac{\exp(V^s(L_{it}))}{1 + \exp(V^s(L_{it}))} \times \frac{\exp(V^{n\ell}(L_{it}))}{\exp(V^{\ell}(L_{it}, q_{it})) + \exp(V^{n\ell}(L_{it}))} \tag{20}$$

$$\Pr(d_{it}) = \frac{\exp(\rho_i(q_{it}))}{\exp(V^s(L_{it} - 1)) + \exp(\rho_i(q_{it}))} \tag{21}$$

Equation 19 is the probability that i searches and `likes` the agent at t. The first term on the right side is the probability that the agent searches, and second is the probability that the agent `likes`, conditional on searching. The following equation for the probability of searching and not `liking` is similar. $\Pr(d_{it})$ is the probability that i decides to pursue going on a date with the agent shown at t, conditional on matching.

Let y^{ℓ}_{it} be an indicator for whether i `likes` the profile shown at time t, y^s_{it} be an indicator for whether i searches, y^m_{it} be whether i matches, and y^d_{it} be the indicator for whether i pursues a date. Note that if $y^{\ell}_{it} = 1$ or $y^m_{it} = 1$, then $y^s_{it} = 1$. Given the observed actions, parameters θ_i, and the probability of each action, the likelihood for an individual is the following.

$$L_i(\theta_i) = \begin{cases} \prod_{t=1}^{T_i} \left[\left(\Pr(s_{it}, \ell_{it}) \Pr(d_{it})^{y^m_{it} y^d_{it}} (1 - \Pr(d_{it})^{y^m_{it}(1-y^d_{it})} \right)^{y^s_{it} y^{\ell}_{it}} \left(\Pr(s_{it}, n\ell_{it}) \right)^{y^s_{it}(1-y^{\ell}_{it})} \right] & TotalViews_i > 0 \\ 1 - (\Pr(s_{it}, \ell_{it}) + \Pr(s_{it}, n\ell_{it})) & TotalViews_i = 0 \end{cases}$$

$TotalViews_i$ is the number of profiles views per session. If $TotalViews_i = 0$, that means i did not search at all during the session.

Ackerberg's Importance Sampling Method

Each individual has a unique draw of ms_i and cs_i, so in order to calculate the likelihood of the data, the value functions need to be calculated for each individual. This poses a computational challenge;

with 66,000 agents in the data, if the value functions take 0.1 seconds to converge for each agent, each iteration in the likelihood optimization function 1.8 hours. For an optimization that takes 1000 iterations to converge, the entire estimation procedure would take 75 days. To reduce the computational burden, I estimate each parameter as a random effect using Ackerberg's importance sampling method (Ackerberg 2005), along with parallelization of value function iteration. Details of this estimation are included in the Appendix. While random effects can capture heterogeneity in the data, it does not allow me to estimate how the parameters vary with population size. For instance, agents in larger markets may inherently be more selective than those in smaller markets. Ideally, I would estimate all parameters as a flexible function of M, but the data is not rich enough for such a flexible model. Therefore, in addition to estimating the parameters separately for men and women, I also estimate parameters separately for agents in small ($M < 11,157$) vs large markets ($M \geq 11,157$).[18]

8 Results

8.1 Parameter Estimates

Table 6 presents the estimates of the parameters from the structural model. Standard errors are estimated from the information matrix. Agents classified as in the small market on average had a population size of 4,000, and agents in the large market have an average population size of 30,000. The key parameters are δ_1, δ_2, and $\bar{s}$. For all agents in both types of markets, the market size factor F^{ms} is positive and significant. This implies that agents who believe they have a larger population size behave as if they have higher expectations for the quality of the profile shown in the next time period. The estimate of $\bar{s}$ informs the effect of competition size. If $\bar{s} > cs$, then competition does not have an effect on an agent's beliefs about whether an agent in his market sees his profile. In small markets, the mean of the estimated distribution of $\bar{s}$ is greater than the average competition size, indicating that that competition does not have a large direct effect on behavior for the average agent. However, in large markets, especially for women, the estimate of the mean of $\bar{s}$ is greater than the average competition size, which reflects that competition does have an effect on beliefs about visibility.

[18]The average population size for all the agents exposed to the treatment is 11,157.

	Men		Women	
Parameter	Mean	SD	Mean	SD
Small Market ($\bar{M}$ = 4,000)				
Market size coefficient (δ_1)	0.251***	4.897***	1.058***	4.670***
	(0.038)	(0.007)	(0.051)	(0.007)
Market size coefficient - Heterogeneity with M (δ_2)	0.029	4.923***	0.200***	4.660***
	(0.038)	(0.023)	(0.049)	(0.029)
Search cost (c^v)	2.299***	1.090***	1.760***	1.170***
	(0.007)	(0.007)	(0.013)	(0.014)
Screening cost (c^m)	3.835***	3.170***	3.687***	2.879***
	(0.039)	(0.025)	(0.046)	(0.030)
Belief about j's search in 10,000's ($\bar{s}$)	2.759***	3.329***	1.208***	3.969***
	(0.066)	(0.155)	(0.247)	(0.360)
Date utility coefficient (λ)	43.417***	26.459***	46.071***	25.656***
	(0.203)	(6.555)	(0.273)	(8.136)
Individual RE for liking (α_i^l)	1.828***	1.840***	0.374***	2.279***
	(0.013)	(0.039)	(0.023)	(0.069)
Log-likelihood	-621,784		-210,240	
Large Market ($\bar{M}$ = 30,000)				
Market size coefficient (δ_1)	0.121**	5.011***	1.028***	4.560***
	(0.061)	(0.011)	(0.076)	(0.011)
Market size coefficient - Heterogeneity with M (δ_2)	0.105**	5.006***	0.230***	4.608***
	(0.060)	(0.038)	(0.074)	(0.044)
Search cost (c^v)	2.109***	1.239***	1.513***	1.359***
	(0.015)	(0.013)	(0.028)	(0.026)
Screening cost (c^m)	3.890***	3.209***	3.920***	2.869***
	(0.062)	(0.040)	(0.068)	(0.044)
Belief about j's search in 10,000's ($\bar{s}$)	3.265***	1.302***	1.379***	3.524***
	(0.024)	(0.019)	(0.257)	(0.388)
Date utility coefficient (λ)	44.702***	27.448***	45.467***	24.475***
	(0.332)	(11.358)	(0.402)	(11.558)
Individual RE for liking (α_i^l)	1.419***	1.951***	0.113***	2.280***
	(0.022)	(0.066)	(0.035)	(0.103)
Log-likelihood	-334,001		-95,701	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Model estimation results. The top half of the table present the parameter estimates for men and women (separately) for agents in markets of below average population size, which I call "small markets". The average market size of the small markets is 4,000. The bottom half of the parameters are for men and women in large markets, where the average population size is 30,000.

8.2 Predicted Actions

The magnitudes of the parameter estimates themselves are not straightforward to interpret, so I illustrate the effects of market thickness on selectivity with the predicted `like` rates, given the parameter estimates, in Figures 11 and 12. These figures illustrate the effect of market thickness for the average agent with the median quality type.

In these figures, the x-axis is the quality of another agent in percentiles, and the y-axis is the relative probability that the agent `likes` the agent of that quality percentile. The lines represent either changes in market size, while holding competition size constant, or competition size, while holding market size constant. To maintain the confidentiality of the data, the baseline `like` probability is obscured. All reported `like` probabilities are relative to the `like` probability of the 10^{th} percentile quality, for the smallest market or competition size depicted in the plot. To illustrate, the plot in the top left corner of Figure 11 depicts how the `like` rate changes for a male agent in a small market when he sees profiles of different qualities. Each line represents a different value of market size, while holding competition size constant at $cs = 4,000$. The plotted `like` rate is the `like` rate relative to the `like` rate for the 10^{th} percentile q_j when the market size is 3,000. Thus, for all plots, the `like` rate for the 10^{th} percentile q_j will always be 0. In a market size of 5,000, the probability that the agent `likes` a 10^{th} percentile q_j is 5% less than when the market size is 3,000. Figure 18 in the Appendix shows that when beliefs about market size increases, women are more likely to search.

In large markets, both the average man and women become more selective when market size increases, and less selective when competition sizes increases. However, the magnitudes of the effects are different for men and women. A 50% increase in market size decreases the absolute `like` rate for the median quality user by about 8% for men, and 2% for women. However, women generally have a lower `like` rate than men, so proportionally, the 2% decrease in the `like` rate is relatively a larger effect for women than the 8% is for men. Conversely, a 50% increase in competition increases the `like` rate for the median quality user by 1% for men, and 5% for women.

These patterns estimated by the model are consistent with the linear regression estimates. Effects on selectivity are larger in magnitude in large markets. In addition, the estimated `like` rates are similar to what is observed in data for both men and women, indicating that the model is a reasonable approximation to the true data generating process. The plots of the predicted `like` rates from the model compared to the actual `like` rates observed in the data are presented in Figure 20 in the Appendix.

A key takeaways from these plots is behavior in small markets is different from behavior in large markets. In small markets, there is the effect of market thickness on selectivity for women with the median quality is much smaller than the effect for women in large markets. In addition, men and women behave very different in responses to changes in market thickness. Men react more strongly to changes in market size, while women are more responsive to changes in competition size.

9 Improving Platform Design

The previous section shows that actions change when *beliefs* about market thickness change. In this section, I simulate how actual changes in market thickness affect outcomes. The goal of these counterfactuals is to inform platform design by first evaluating how changes in market thickness affect matching outcomes in equilibrium, and second, measuring how certain platform design features can affect matching, while promoting platform membership.

I compare all counterfactuals to a baseline, which a market of population size M with $0.75M$ women and M men. Rather than selecting a baseline of a market with the same number of men and women, I choose to simulate markets with more men than women, since that is more realistic to conditions that online dating platforms face. I compare the counterfactuals in large markets ($M = 30,000$) and small markets ($M = 4,000$).

To calculate the counterfactuals, I first solve for the equilibrium for a market with population size M with m men and w women by iterating the value functions until the actions of women equal men's beliefs about women's actions, and vice versa. I then simulate the actions for the m men and w women for $T = 500$, meaning they have a maximum of 500 search opportunities. Details on estimation of the counterfactuals are provided in the Appendix. Note that the outcomes of the simulations should be interpreted with the possibility of many equilibriums, and the estimated equilibrium in this paper may just be one of them.

The baseline market is 3,000 women and 4,000 men for a small market, and 22,500 women and 37,500 men for a large market. The outcomes variables I consider are the percentage change in the number of matches a man or woman gets compared to the baseline; the change in average match quality, conditional on getting a match; and the relative change in the likelihood that an individual finds a date. To find a date, the agent has to pursue a date with his match, and his match must also pursue a date with the agent. I display these various metrics because different platform may

	% Δ Matches		% Δ Match Q		% Δ Date	
	M	W	M	W	M	W
C1: Increase market thickness	-12.2	-17.7	0.1	-3.6	-12.0	-17.5
C1 & increase $\bar{L}$	136.3	121.6	-0.3	-5.7	66.0	55.6
C2: Gender gating (men)	10.4	-17.2	-0.6	-13.4	-7.5	-30.6
C2 & increase $\bar{L}$ for women	60.1	20.1	-1.3	-9.2	20.0	-10.0

Table 7: Small markets (M = 4,000): Percent difference in various outcome measures for several counterfactuals. All compared to a baseline market with 3,000 women and 4,000 men. The first column is the percentage change in matches for each individual. The second column is the percentage change in the average quality measures of the matches, conditional on getting a match. The last column is the percentage change in the likelihood that an agent gets a date (both agents must pursue a date with each other).

	% Δ Matches		% Δ Match Q		% Δ Date	
	M	W	M	W	M	W
C1: Increase market thickness	0.4	-5.9	0.8	6.7	34.3	25.9
C1 & increase $\bar{L}$	205.7	186.6	2.1	11.5	122.9	108.9
C2: Gender gating (men)	16.1	-12.9	1.6	2.4	10.7	-17.0
C2 & increase $\bar{L}$ for women	104.4	53.3	-0.3	11.7	89.3	42.0

Table 8: Large markets (M = 30,000): Percent difference in various outcome measures for several counterfactuals. All compared to a baseline market with 22,500 women and 37,500 men.The first column is the percentage change in matches for each individual. The second column is the percentage change in the average quality measures of the matches, conditional on getting a match. The last column is the percentage change in the likelihood that an agent gets a date (both agents must pursue a date with each other).

have different objectives. For example, some firms may prioritize maximizing matches, another firm may prioritize maximizing the number of dates, while others want to maximize the quality of the matches. The goal of the counterfactuals presented in this paper is not to prescribe the optimal solution for the firm, but to show that market thickness and policies can have different effects on matching and dating, and firms can design their policies to fit their needs. I describe the different counterfactuals and their results in more detail in the following section.

9.1 Increase in Market Thickness

The first counterfactual I consider is what happens to matching and date outcomes when there are more men and women on the platform. The platform monetizes from premium users, so the platform has an incentive to continue growing, even after it has reached critical mass. This counterfactual simulates a 25% increase in both men and women on the platform for small and large markets.

The first row of Tables 7 and 8 show that increasing market thickness has different effects in small vs large markets. In small markets, when compared to the baseline market of 3,000 women and 4,000 men, increasing the number of men and women by 25% leads to 12% fewer matches for men and 17% fewer matches for women, and a similar decrease in dates. The likelihood that a man finds a date during the search session decreases by 12%, and the likelihood for women decreases by 18%. In larger markets, market thickness has a smaller effect on matching and dating outcomes. Women have slightly fewer matches (-6%), but they become more likely to find a date. To get a sense of why matching outcomes are worse, consider Figure 13, which plots how selectivity changes when market thickness increases. The x-axis in these figures is the quality type percentile of the individual whose profile is viewed, q_j, and the y-axis is the change in the probability that an agent i with a median q_i `likes` j. The interpretation of this figure is that when market thickness increases, men become less likely to `like` lower quality type women and more likely to `like` high quality type women, and women become more likely to like lower quality type men and less likely to `like` high quality type men. Since both men and women are getting fewer matches, the chances of finding a date decreases. There is also heterogeneity how the increased market thickness affects agents of different quality types. Figure 14 shows the percentage change in probability of finding a date as a function the agent's quality type. Since women become more likely to `like` lower quality men, lower quality men experience the largest increase in the probability of finding a date. On the other hand, since men become much less likely to `like` lower quality women, lower quality women become much less likely to find a date.

However, in large markets, increasing market thickness decreases womens' matches by 6%, but increases their match quality by 7%, and both men and women are more likely to find a date. The difference in outcomes between large and small markets can be attributed to competition playing a larger role in large markets. A 25% increase in a large market is a much larger absolute increase in a smaller market. Since agents do not adjust their search intensity that drastically, and the platform's algorithm does not change, when there are 25% more people in large markets, the chance that two agents match decreases because they are less likely to be served each other's profiles. In the large market equilibrium, men do not become as selective as their counterparts in small markets, as shown in Figure 15.

9.1.1 Increasing the `like` limit for Both Genders

Due to agents adjusting their selectivity, the previous counterfactual showed that adding more people to the platform can reduce matching quantity and quality for agents in small markets. One implication of this could be for the platform to prevent new users from joining in small markets. However, this is not ideal because (1) platforms may want to focus on growth in small markets and (2) barring new members may mean a loss in potential revenue. So how can the platform better matching outcomes while continuing to grow? Since selectivity is driving the results, one way that this platform can change selectivity is through the `like` limit. Increasing the `like` limit can help agents not only increase their `like` rates overall, but also can make them become more likely to `like` higher quality users. Thus, increasing the `like` limit is one policy that the platform can implement to improve matching outcomes. The second row in Tables 7 and 8 show the outcomes for when market thickness increases by 25%, and the cap on the number of `likes` doubles for all agents.

When the like limit increases for both men and women, the number of matches increases, in both large and small markets. In small markets, the average match quality slightly decreases, but the difference does not seem large enough to be significant. However, in large markets, the average match quality increases for women.[19]

9.2 Gender Gating

Another set of counterfactuals that I simulate are about increasing agents on one side of the market. Many marketplaces, especially dating markets, have imbalances in the number of agents on each side of the market. To try to balance the ratio, platforms may target marketing towards women or disincentivize men from joining. I refer to selective targeting towards one side of the market as “gender gating”. I simulate how increasing the number of women on the platform by 25%, while holding the number of men constant, affects matching outcomes for agents in small and large markets.

Row 3 in Tables 7 and 8 display the results of this simulation. When men are prevented from joining the platform, women in both small and large markets get fewer matches and are less

[19] Match quality increases for men as well, but it is unclear if it is significant.

likely to find a date, as expected. Interestingly, in small markets, men get more matches, but do not get better quality matches. In addition, a man becomes 7.5% less likely to find a date. The reasoning behind this is that when men have more choices, their belief about the quality of the next profile increases, which may increase their value of search. Thus, conditional on finding a match, they are less likely to accept when they have more potential matches, as the expected utility from future search increases. Since men become more selective and are less likely to propose a date, women become less likely to match and find a date. Figure 21 in the Appendix shows how their selectivity changes.

Women in large markets get 13% fewer matches, and 17% fewer dates, but conditional on finding a match, they get a slightly better quality matches (2.4%). Men in large markets are unanimously better off when they have more choice; they get more matches, higher match quality, and are more likely to find a date.

9.2.1 Increasing the `like` limit for Women

While gender gating worsens matching outcomes for women, the platform may still want to implement gender gating since improves match quantities for men. In this counterfactual, I show that increasing the `like` limit for women can improve matching outcomes for women under the gender gating policy.

Since women experience the largest decline in match quantity and quality, this counterfactual considers doubling the `like` limit for women, while holding the limit constant men, in addition to gender gating. Row 4 in Tables 7 and 8. I find that increasing the `like` limit for women mitigates some of the negative effects of gender gating. For women in small markets, increasing the `like` limit, in addition to gender gating, decreases match quality by 9% and decreases the probability of finding a date by 10%, as opposed to 13% and 31%, respectively, when the `like` rate for women is 100. Increasing the `like` limit has further positive effects for women in large markets. Their `like` rate increases by 11% and chances of finding a date increases by 42%, as opposed to 2.4% and -17%, respectively.

9.3 Discussion

In summary, given the causal effects of market thickness estimated from the model, the counterfactuals simulate matching and dating outcomes in the equilibrium. They show that the same policy implemented in small versus large markets may lead to different outcomes, indicating that platforms should customize policies based on market thickness. The main difference between small and large markets is their sensitivity to the direct effect of competition: increasing competition has a smaller direct effect for agents in small markets than agents in larger markets.

There are three main takeaways from the counterfactuals. (1) Increasing the number of people on the platform may reduce match quantity and quality. In small markets, increasing the number of men and women by 25% leads to 12% fewer matches for men, and 17% fewer matches for women. (2) Increasing the number of women only on the platform by 25% does not significantly increase match quality for men (-0.6% change for men in small markets, 1.6% in large markets). (3) The last, and most important takeaway is that all these effects are driven by changes in selectivity. By inducing agents to become less selective through changing their like limit, the firm is able to increase market thickness or implement gender gating without significantly worsening match quantity and quality. In other words, changing selectivity (i.e. increasing the like limit in this case) can mitigate negative effects of increasing market thickness and gender gating.

10 Conclusion

Understanding search in large, decentralized matching markets is important to the success of the platform, as agents search to find a match. Search in matching markets is complicated by the fact that matching is two-sided. An individual's decision in how much to search and to propose a match to depends on his beliefs about the availability of other agents on the platform. This papers studies how the role of beliefs about market thickness, defined as the number of agents on the same and opposite sides of the market, affects search and selectivity, and guides how firms should design their platforms in light of this effect. I observe that individuals who have more choice (competitors) are also more (less) selective. As matches are two-sided, individuals that are more selective may end up with worse matching outcomes, as the people they `like` are less likely to `like` them back. Conversely, competition may make individuals less selective, which increases their changes of matching. This observation challenges the common assumption and theoretical finding that agents have better matching outcomes when they have more potential matches, and worse matching outcomes when they have more competitors. Using data from an online dating app, this paper empirically evaluates the impact of market thickness on an individual's search and matching behavior, with the goal of informing platform design. To simulate the matching outcomes of different policies, I build a structural model of search and selectivity which incorporates beliefs about market thickness. Because market thickness is an endogenous variable, I run a large-scale field experiment to exogenously vary beliefs in order to estimate the parameters of the model. I document a causal effect between an individual's belief about how many potential matches and competitors and their behaviors and outcomes on the platform. When agents believe they have more choices, hence a larger market size, they become more selective in who they want to match with. On the other hand, when they believe they have more competitors, they become less selective.

The counterfactuals considered in this paper revolve around increasing market thickness and gender gating. Matches and dates are modeled as a statistical outcome from search and selectivity. I find that in small markets, increasing market thickness has a negative effect on both matches and dates for men and women, which suggests that the platform should limit new members. However, preventing people from joining the platform may mean a loss in potential revenue, as the platform monetizes from premium users. I show that increasing the number of `likes` an individual can send can increase match and dating outcomes while still allowing people to enter the market. In addition, when there are more women on the platform, men do not necessarily get higher quality matches, as predicted by theory.

A limitation of this paper is that I cannot observe when dates happen, which is a common problem in online dating sites. Firms cannot observe when a match on the platform results in a date or marriage, as people often communicate with their matches through offline channels. Due to the lack of data, I made strong assumptions about the likelihood of a match resulting in a date. Another limitation is that the current model does not include learning. Since market size affects the belief about the quality distribution, if in reality, market size does not change the distribution of quality (i.e. the new users are of the same quality type as the current users), the individual may adjust his beliefs over time. Thus these results are more applicable to short-term changes in market thickness, such as daily or weekly fluctuations.

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11 Appendix

11.1 Natural Variation in Market Thickness

I use a 2-week sample of the historical data to provide more information on how much the market thickness naturally varies in this setting. The sample is all users who have opened the app from one of the countries the experiment is implemented in in the two-week window. For each location[20], I determined the number of distinct users who opened the app, for each day-hour. I then calculated the average and standard deviation of number of distinct users over each location - day. Figure 16 plots the coefficient of variation ($\frac{SD}{Mean}$) for each hour in a selected location that seems representative of all other locations. That is, each observation in that plot is the standard deviation of the number of distinct users who open that app from that location-hour divided by the average number of users who open the app from that location-hour. There appears to be significant variation in the number of users at any given hour. This gives an idea of much the market thickness varies for a given hour. To compare this to the experiment, the maximum variation in the experiment is 25%. Thus much of the natural variation at the hour level is greater than the variation induced by the experiment.

[20] 25x25 mile

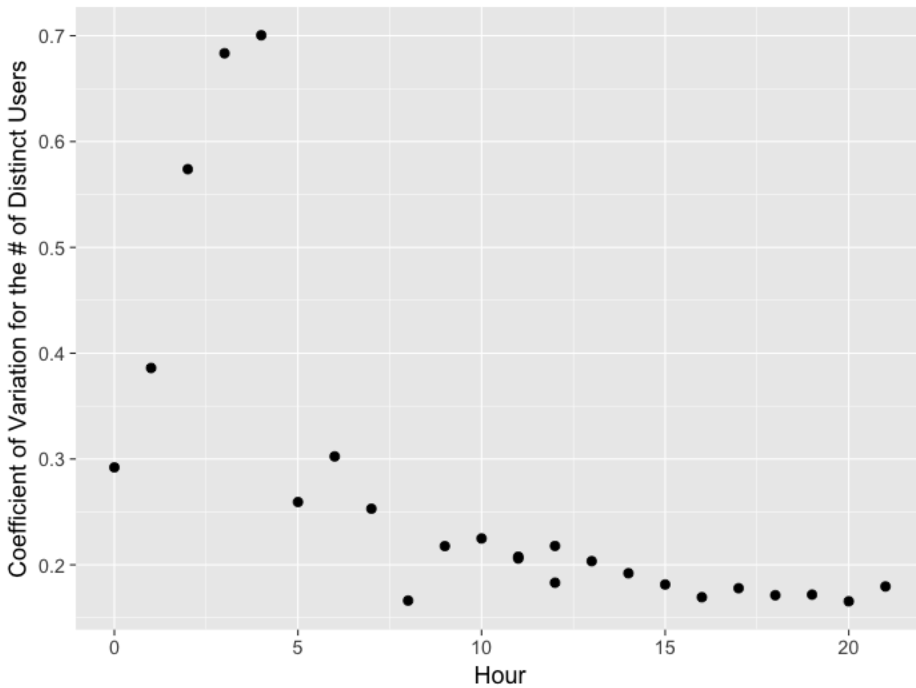

Figure 16: The coefficient of variation in the number of distinct users who open the app for each hour of the day, averaged over a two-week period. The sample in this figure is all users who open the app from a location in one of the countries that the experiment is implemented in during the two-week time period. The selected location to be representative of the other locations. The time zone has been shifted to preserve confidentiality.

11.2 Randomization Check

I ensure the treatment within the treatment group is sufficiently randomized by comparing the correlations between the treatment variables and pre-treatment user characteristics.

	ρ	P-val
F^{cs}	0.001	0.552
Age	0.002	0.079
Gender	0.000	0.940
Account Age	0.000	0.867
Profile Views	0.000	0.839
Like Rate	-0.002	0.168
Matches	-0.000	0.803

Table 9: The correlation between the market size factor F^{ms} and other treatment variables, and pre-experimental characteristics.

The correlations are shown in Table 9. Table 9 confirms that there is no correlation between F^{ms}, F^{cs}, user characteristics, and pre-treatment behavior, such as the number of profiles the users have viewed, their `like` rates, and the number of matches they've made.

	Dependent variable:	
	q_j	
	(1)	(2)
Index	-0.00000^{***}	
	(0.00000)	
q_i		0.176^{***}
		(0.021)
Agent FE	Y	N
Location FE	N	Y
Filter FE	N	Y
Observations	19,877,176	20,932
R^2	0.780	0.240
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 10: Linear regressions of q_j, the quality of the profile shown to i, on the order that the profiles are shown (Index) and on i's quality (q_i). The coefficient of Index in Column 1 is -1.519e-06. Column 1 includes agent fixed effects (standard errors are clustered by agent), and Column 2 uses only the first profile view for each agent.

11.3 Structural Model

11.3.1 Bayesian Game

I describe this setting more formally as a Bayesian game of incomplete and imperfect information. Each agent i has a type λ_i, where $\rho_i(q) = \lambda_i q$. In other words, each agent values going on a date with another player of type q differently. Each agent knows his own λ_i but not those of other agents. q can be though of as a noisy signal for λ. i also does not know the history of any other agents.

When agent i, with quality q_i meets another agent j with quality q_j, i knows ρ_{ij}, i's date utility from going on a date with j, but does not know ρ_{ji}, j's date utility. Thus, he has incomplete information about ρ_{ji} so he does not know how j will behave. But given q_j, i has beliefs about λ_j, and thus, also has beliefs about whether j `likes` i.

This Bayesian game consist of

- A set of agents $\mathcal{I}$
- A set of actions for each agent i: $a_i = \{l, nl\}$
- A set of states: $x = \{L, ms, cs\}$
- A set of types for each i: $\lambda_i \in \mathbb{R}$
- A probability distribution over q: $f(q)$
- Each i has beliefs over the likelihood that another agent of type q_j will `like` i
- A payoff function for each i and strategy, given states and beliefs about another agent of type q_j: $u_i^l(q_j, L, ms, cs), u_i^{nl}(q_j, L, ms, cs)$

In the BNE, each agent with type q has a strategy that maximizes his expected utility for each quality of profile that he sees. Since this is a finite game (there are a finite number of agents, and actions), a BNE is guaranteed to exist. However, because the type set (λ) is not compact, then a pure strategy BNE is not guaranteed to exist.

11.3.2 Ackerberg Importance Sampling Method

I estimate the random effects using Ackerberg's importance sampling method. In some applications, the set of draws from the importance density is not individual specific. In words, $\theta_{ir} = \theta_r$ for all i. To promote more mixing, in this paper, I made separate draws of θ_{ir} for each individual. Below are the steps for each individual i with parameters θ_i.

1. Make R draws of $\theta_{ir} \sim f(\bar{\theta}_h, \Sigma_h)$ where h represents the importance density. $\Omega_h = \{\bar{\theta}_h, \Sigma_h\}$ denotes the hyperparameters of the importance density.

   - The search and screening costs, and $\bar{s}$ are non-negative, so those are drawn from truncated normal importance densities, while $\alpha^l, \delta_1, \delta_2, \lambda$ have unbounded support. The latter parameters are drawn from a multivariate normal distribution. To simplify computation, the covariance between $c^v, c^m, \bar{s}$ are fixed to be 0, while the covariance matrix for $\alpha^l, \delta_1, \delta_2, \lambda$ is estimated. Σ_h denotes the covariance matrix for all parameters, while the covariance between $c^v, c^m, \bar{s}$ are fixed to be 0.

2. Compute the likelihood $\mathscr{L}_i(\theta_{ir})$ for all R draws.

3. Let $\Omega_g = \{\bar{\theta}_g, \Sigma_g\}$ be the hyperparameters of θ. Compute $\mathscr{L}_i(\Omega_g, \theta_i) = \frac{1}{R}\sum_{r=1}^{R} \mathscr{L}_i(\theta_{ir}) \times \frac{h(\theta_{ir};\Omega_h)}{g(\theta_{ir};\Omega_g)}$

4. Maximize the following log likelihood.

$$\max_{\Omega_g} \sum_i \log \mathscr{L}_i(\Omega_g)$$

In this paper, some of the parameters are restricted to be positive, such as $\bar{s}$, the screening cost, and the search cost, while others have infinite support. Since I cannot draw from a multivariate distribution that is truncated for some parameters, I set the diagonals for the covariance matrix to 0.

11.3.3 Estimating Beliefs from Pre vs. Post Experiment Data

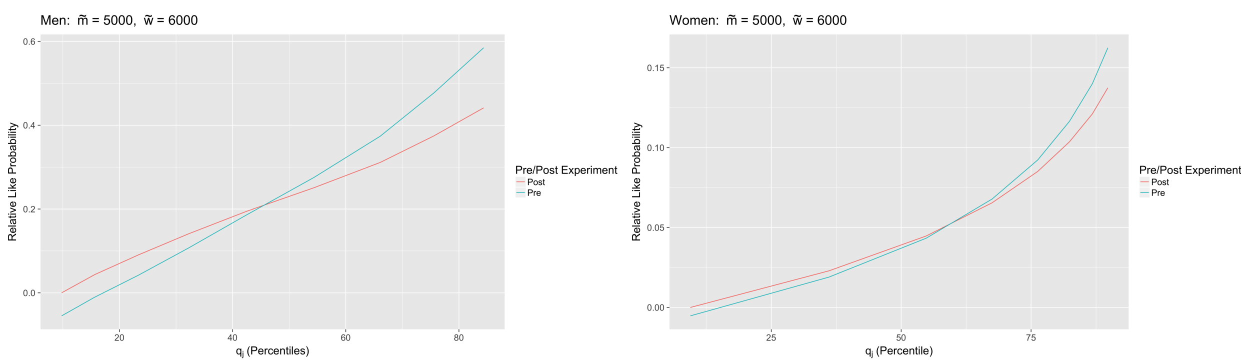

Figure 17: A comparison of the observed `like` rates using pre-experimental and post-experimental data for men (left) and women (right). The plotted `like` probability is relative to the `like` probability for the 10^{th} percentile quality using in the post-experimental data.

11.3.4 Value Functions for Search

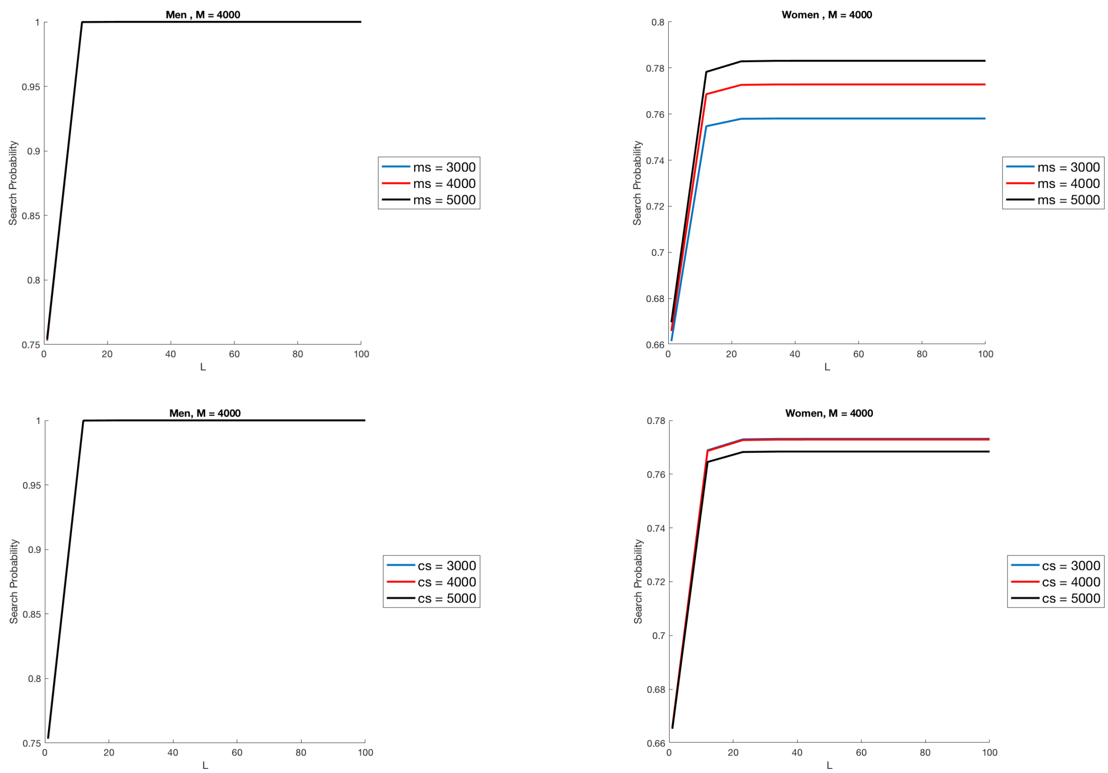

Figure 18: Search and market size in a small market.

11.3.5 Comparing Model Estimates to Observed Data

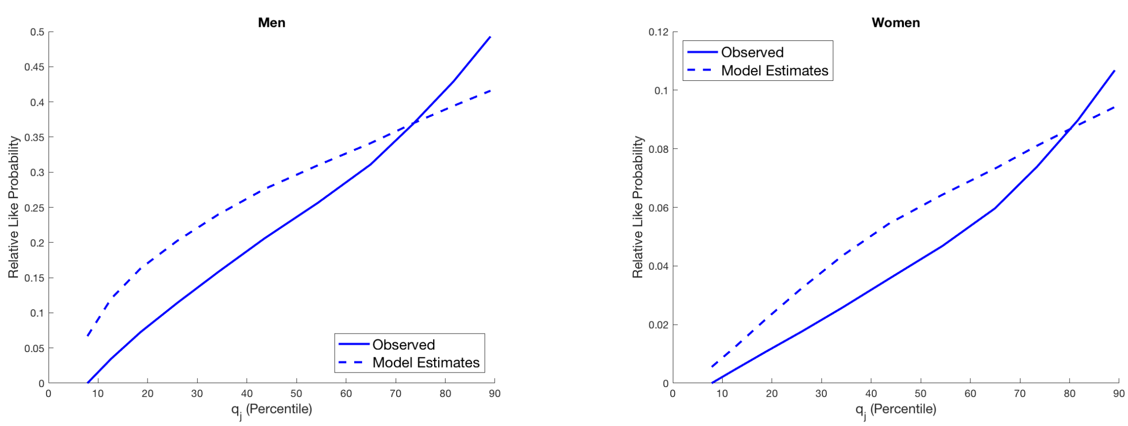

Figure 20: Model estimates versus observed data.

Figure 20 shows the predicted `like` rates based on model estimates versus the observed `like` rates. The goal of these plots is to evaluate whether the model and estimates are able to recover observed patterns in the data. I do by plotting the probability that an average man or woman `likes` another agent of type q_j for the observed data, and as predicted by the model estimates. The observed data is plotted based on the following logistic regression.

$$Like_{ij} = \beta_0 + \beta_1 q_i + \beta_2 q_j + \beta_3 q_j^2 + \beta_4 ms_i + \beta_5 cs_i + \epsilon_{ij} \tag{22}$$

The graph on the left in Figure 20 plots the `like` probability for men, and for the women on the right. The x-axis is the quality of an agent that an agent sees, and the y-axis is the relative probability that the agent `likes` that profile for the an agent with an average quality and with an average market and competition size. The `like` probability (or `like` rate) is relative to the `like` probability for a 20^{th} percentile quality profile. The solid line is the observed data, which is the predicted `like` probability from Equation 22, and the dotted line is the predicted `like` probability from the model.

Figure 20 shows that the model does a decent job at simulating the data generating process to produce the observed data. Especially for women, the model estimates are very similar to the observed data.

Counterfactual Estimation

11.3.6 Equilibrium Estimation

While the equilibrium was not calculated in order to estimate the model parameters, the equilibrium must be calculated for counterfactual analysis. The general idea for equilibrium is that the an agent's beliefs about the behavior of an agent on the other side of the market equals the actions of that agent, and vice versa. When agent i changes his actions in response to a change on the platform, the other agent j's picks the optimal action in response to i's actions. In response, because j changed his actions in response to i, i then changes his actions in response to his beliefs about j's behavior. This sequence iterates until actions and beliefs converge. The following provides details on this estimation procedure.

For ease of exposition, I illustrate the procedure with two agents: man i and woman j. Let policy p denote the original policy, and p' denote the new policy. $\pi_i^{like}(q_j|\theta, p, b_{ij}^{like}, b_{ij}^{search})$ is the probability that i `likes` j, given parameters θ, policy p, i's beliefs about whether j `likes` i, conditional on searching b_{ij}^{like}, and i's beliefs about j's search intensity b_{ij}^{search}. $\pi_i^{search}(q_j|\theta, p, b_{ij}^{like}, b_{ij}^{search})$ is the probability that i searches in each time period.

1. Set i's initial beliefs about j's actions: $b_{ij}^{like(0)} = \pi_j^{like(0)}$, $b_{ij}^{search(0)} = \pi_j^{search(0)}$

2. Calculate $\pi_i^{like(1)}(q_j|\theta, p, _{ij}, \pi_j^{like(0)}, \pi_j^{search(0)})$ and $\pi_i^{search(1)}(q_j|\theta, p, \pi_j^{like(0)}, \pi_j^{search(0)})$.

3. Given $\pi_i^{like(0)}$ and $\pi_i^{search(0)}$, calculate $\pi_j^{like(1)}(q_i|\theta, p, \pi_i^{like(1)}, \pi_i^{search(1)})$ and $\pi_j^{search(1)}(\theta, p, \pi_i^{like(1)}, \pi_i^{search(1)})$

4. $\pi_j^{like(0)} = \pi_j^{like(1)}$, $\pi_j^{search(0)} = \pi_j^{search(1)}$, $\pi_i^{like(0)} = \pi_i^{like(1)}$, $\pi_i^{search(0)} = \pi_i^{search(1)}$

5. Repeat steps 2-4 until π_i^{like},π_i^{search}, π_j^{like}, π_j^{search} converge.

11.3.7 Simulating Agent Actions

Given the value functions estimated in equilibrium, I then simulate behavior for m men and w women. The quality type of each simulated agent is drawn from the same observed distribution of q for the respective gender. Similarly, their parameters $\theta_i = \{\delta_{1i}, \delta_{2i}, c_i^v, c_i^m, \bar{s}_i, \lambda_i, \alpha_i^l\}$ are drawn from the estimated distributions.

I simulate $T = 500$ time periods. I list the simulation steps from the perspective of an agent i.

1. At time t, i has L_{it} `likes` left and decides whether to search. The probability that he searches is determined by his value functions estimated in the previous equilibrium step. If $L_{it} = 0$, then he cannot search and his session ends.

   (a) If i decides to not search, his session is over and he does not search for the remaining 499 periods.

2. If i searches, he is shown a randomly drawn (without replacement) agent's profile from the set of agents of the opposite gender. Because it is drawn without replacement, he will never see the same profile twice, much `like` the app. I denote this agent by j.

3. He observes q_j.

   (a) If he `likes` j and j has `liked` him at time $t' \leq t$, then i and j match at t.

i. i decides to propose a date with probability $\frac{\exp(\lambda_{1i}q_j)}{\exp(\lambda_{1i}q_j + V^{search}_{i,t+1})}$. j proposes a date with probability $\frac{\exp(\lambda_j q_i)}{\exp(\lambda_j q_i + V^{search}_{j,t+1})}$. If they both propose a date, the date is realized. The search session ends for a user once he pursues a date, regardless of whether the date is realized.

ii. If i does not pursue a date, then $L_{i,t+1} = L_{it} - 1$, and he goes back to step 1 at $t+1$.

(b) If i does not `like` j, he goes back to step 1 at $t+1$.

I want to highlight a couple differences between the simulation and the model. First, in the simulation, profiles are shown are completely random. However, in the app, the matching algorithm is more likely to show a profile of similar quality. This was done purely to simplify computation. Future work will include incorporating the matching algorithm into the counterfactual simulations. Second, the model considers only matches that were formed instantaneously. For instance, if i `liked` j at time t and j `liked` i at time $t' > t$, then the match would have been formed instantaneously from j's perspective, but not i's. Thus, in the model, j would have matched with i, but i could not have matched with j. Modeling only instantaneous matches greatly simplifies the model, and since the subset of treated users is so small relative to the entire population, agents rarely saw profiles of other agents who were also in the treated sample. However, in the simulation, every agent in the market is modeled. Thus, the model needs a way to resolve matches when they do not occur instantaneously. In the simulation, if agent i views agent j at t but also matches with agent k at t, he considers going on a date with k, and stops search if a date is realized. If i matches with multiple agents at t, then he considers proposing a date to each of them. In this case, i may go on multiple dates. If at least one date is realized, i ends his session at $t+1$.

11.3.8 Changes in Selectivity - Gender Gating

Figure 21 displays how selectivity changes for men and women in a small market when there are more women on the platform. The x-axis is the quality percentile of a profile they are shown, and the y-axis is the change in the `like` probability, compared to the baseline counterfactual. The figure shows that when there are more women on the platform, women become more likely to `like` lower quality men and less likely to `like` higher quality men, while men become much less likely to `like` lower quality women. This change in selectivity results in the matching outcomes presented in the first row of Table 7. The line is the change in the `like` probability for the quality profile

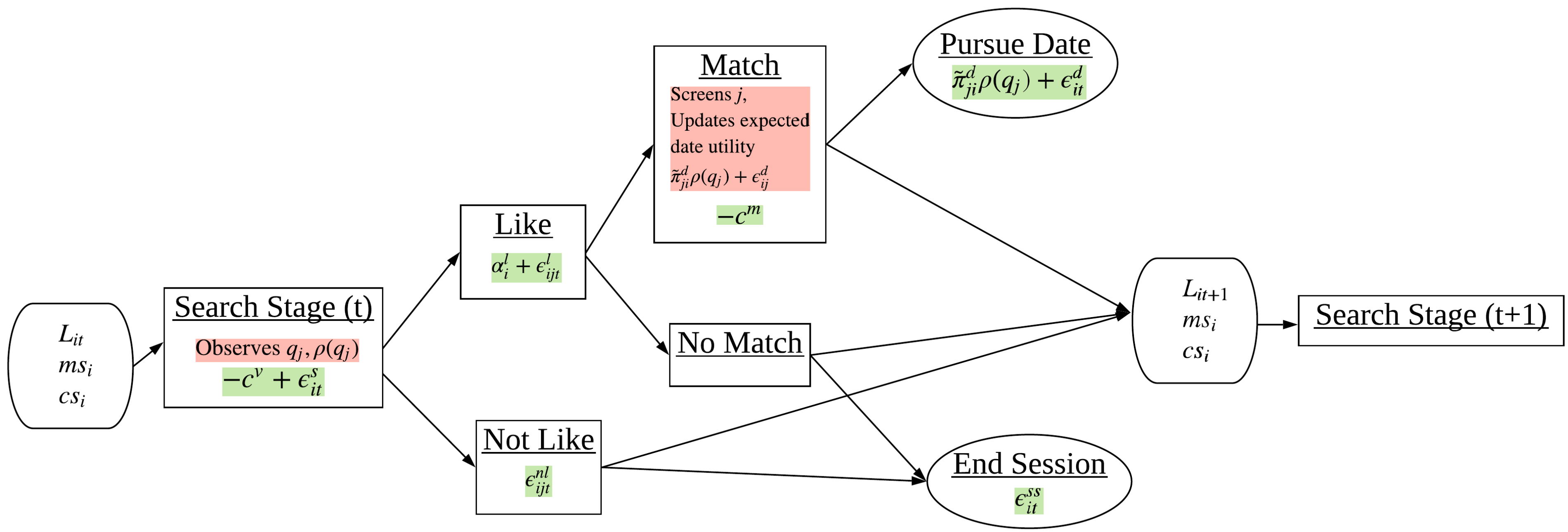

Figure 10: Detailed illustration of what happens during each stage of the model, and the current period utility the agent receives. Ovals are end stages. The text highlighted in green is the utility received, and text highlighted in red is the action that happens in the corresponding stage.

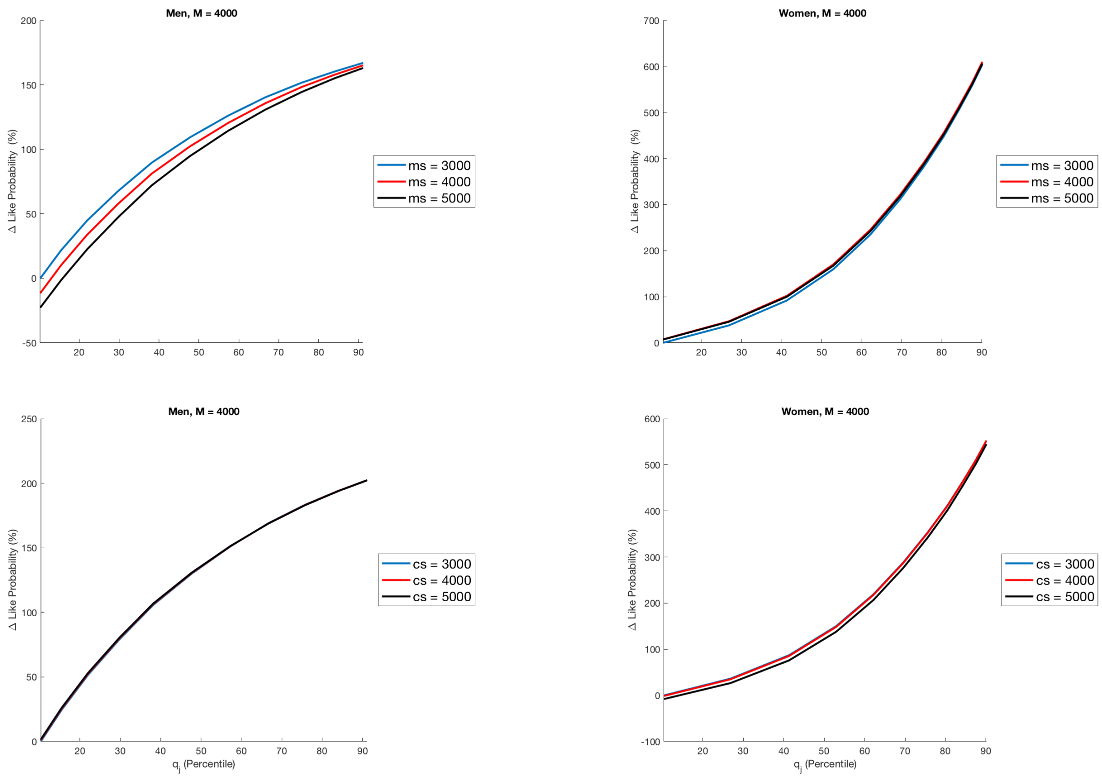

Figure 11: How selectivity changes with market size and competition size for agents in a small market.

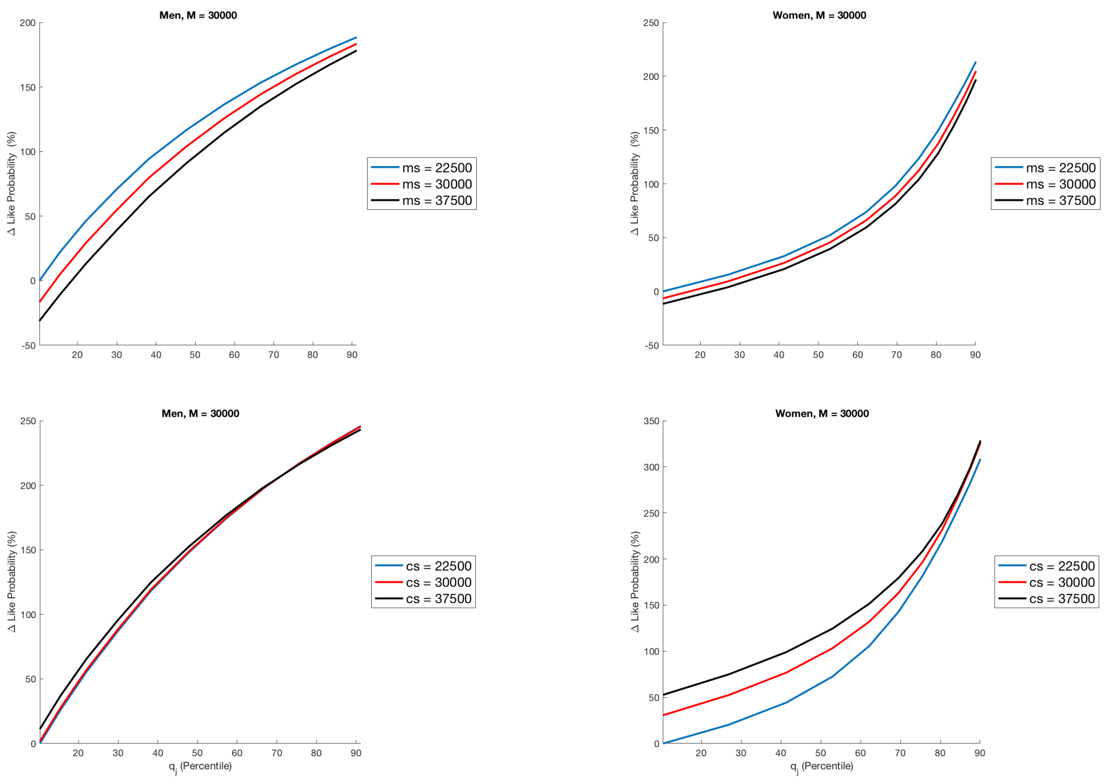

Figure 12: Selectivity and market size in a large market.

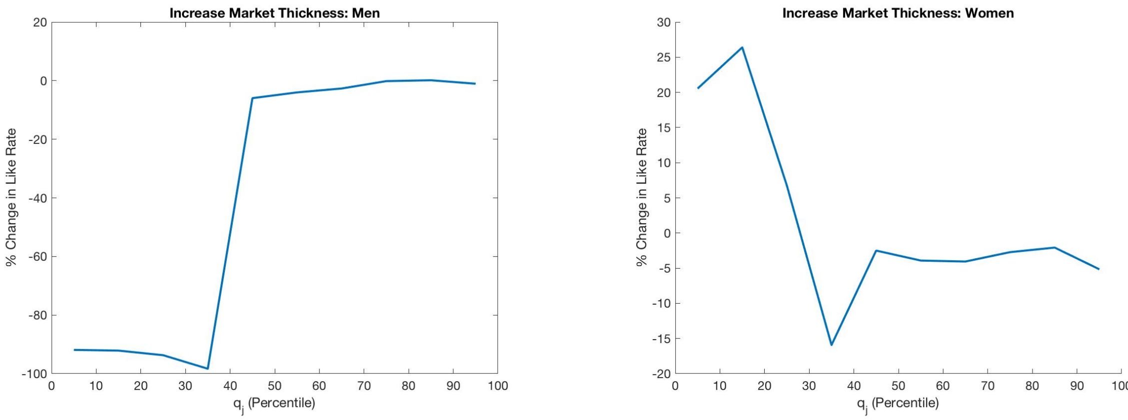

Figure 13: The change in the equilibrium probability that an average agent `likes` another agent with quality q_j for men (left) and women (right).

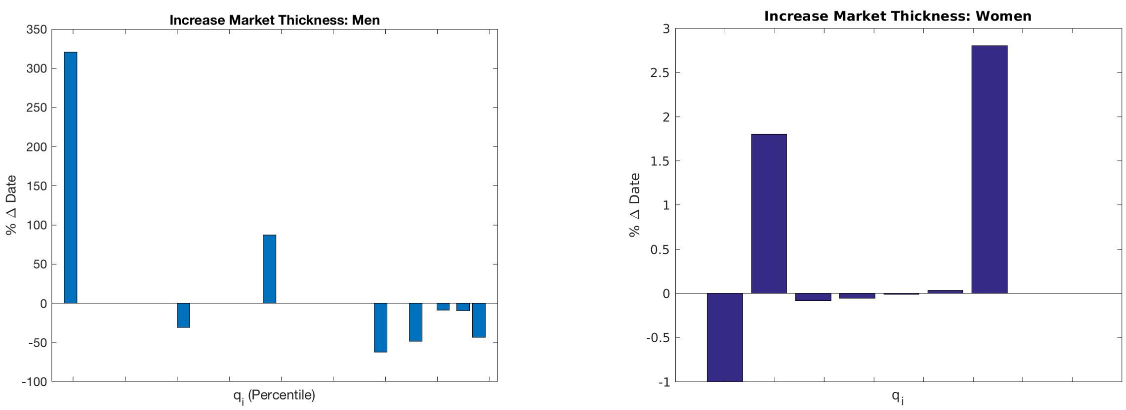

Figure 14: Percentage change in the likelihood of finding a date when market thickness increases, for both men (left) and women (right). The x-axis is the quality of the agent i, and the y-axis is the change in the likelihood of finding a date for the corresponding quality type q_i.

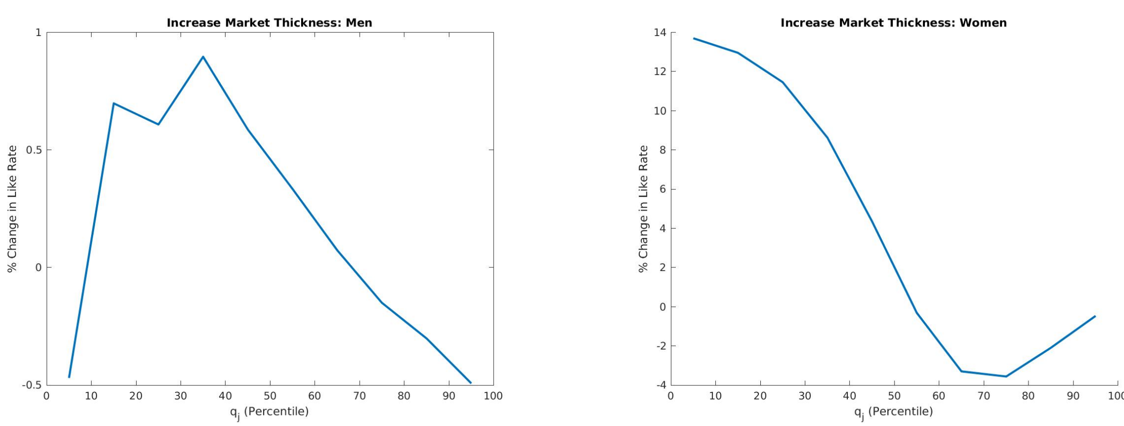

Figure 15: Large market: the change in the equilibrium probability that an average agent `likes` another agent with quality q_j for men (left) and women (right).

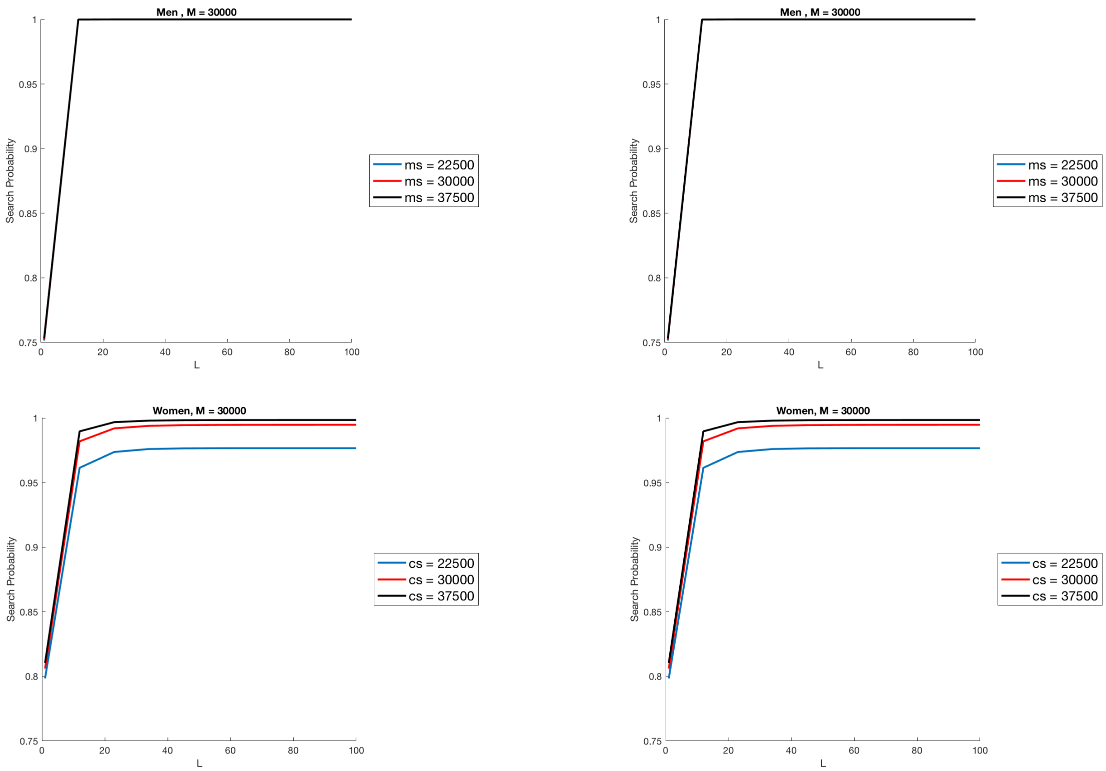

Figure 19: Selectivity and market size in a large market.

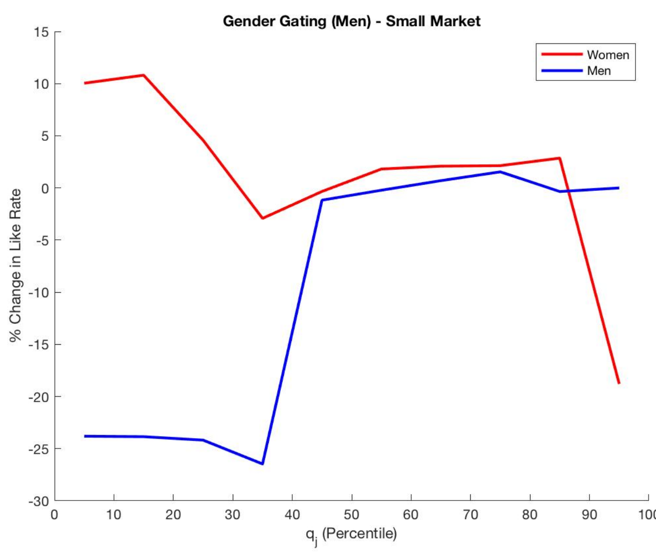

Figure 21: The change in the equilibrium probability that an average agent `likes` another agent with quality q_j for men and women.