The More You Know: Information Effects on Job Application Rates by Gender in a Large Field Experiment*

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Abstract

This paper presents the results from a 2.3 million person field experiment that varies whether a job seeker is shown the number of applicants for a job posting on a large job posting website, LinkedIn. This intervention increases the likelihood a person will start/finish an application by 0.6%-1.9%, representing an economically significant potential increase of over a thousand applications per day. This increase is greater for female applicants. Firms in industries that are highly represented on this job posting website may be particularly interested in this low cost, light touch intervention that potentially increases the number of female applicants.

1 Introduction

There is a documented wage gap in the U.S. with women earning about 30% less than men (Goldin, 2014). To study this issue, previous research has focused on differences in human capital accumulation and firm side discrimination. However, a more recent stream of laboratory produced research has found that women tend to be more ambiguity/risk averse than men, and that women dislike competition more than men do (Azmat and Petrongolo, 2014; Bertrand, 2011; Croson and Gneezy, 2009; Eckel and Grossman, 2008). These behavioral differences observed in the lab present another possible explanation for differences in occupation choices and competitive performance in the real world. To understand the extent to which these laboratory results translate to real-world behavior, several large scale field studies have been conducted (Chen and Konstan, forthcoming; Samek, 2015; Flory et al., 2015). This paper fits within this field of research by examining behavioral motivations across genders in a large scale field study with real labor market implications.

In many theoretical models job seekers are generally modeled as facing decisions with both known risks, such as the likelihood of a job offer, and known utilities regarding prospective positions.[1] However, in reality, job seekers face many unknown risks or "ambiguity" about the probability of an offer or the utility of a position. If job seekers are ambiguity averse or if they use signals to update their beliefs, then these theoretical models lose some of their predictive power. This paper is intended to bridge the gap between theoretical assumptions and real-life behavior by analyzing the job search behavior of over 2.3 million job seekers viewing over 100,000 job postings on the website LinkedIn in March 2012. Specifically, I compare the behavior of job seekers based on the information they receive. This study varies whether job seekers are shown the number of people who previously began an application for a viewed posting.

Intuitively, adding extra information may change either the cost of applying or the expected benefit in terms of obtaining the position. Behavioral

[1]See Galenianos and Kircher (2009); Mortensen (1970); Das and Tsitsiklis (2010); Chade and Smith (2006); Weitzman (1979); Kohn and Shavell (1974); Telser (1973); Nachman (1972) and Stigler (1961).

economics offers several theories from which we can derive predictions about the effect of knowing the previous number of started applications on the likelihood of application. Specifically, I focus on the following three in this study: (1) ambiguity aversion, (2) competition avoidance, and (3) herding. Ambiguity aversion suggests having more information will reduce ambiguity and in turn increase application likelihood. Competition avoidance suggests job seekers may try to avoid competition when there is a high number of started applications. On the other hand, herding suggests seekers will apply to more popular postings. All three behaviors may be observed in the data, but from a policy perspective it is important to know which one has the largest average effect on job application rates, and in particular if there are heterogeneous treatment effects for men and women.

Understanding the interaction between behavioral factors and job search behavior could be used to create a welfare gain from a better functioning labor market. If ambiguity aversion dominates, then adding more information to the job posting may increase the likelihood of application, especially for women. In turn, this may enhance welfare by both increasing the thickness of the market and decreasing the gender occupation gap.[2] By contrast, if competition avoidance dominates there may be a welfare gain from decreased congestion, but also a decrease in the number of female applicants. Last, if herding behavior dominates, the resulting congestion may create a welfare loss.

The results from this experiment show no strong pattern of either competition avoidance or herding for either gender. However, interestingly, the results show that the addition of information increases the likelihood of starting or finishing an application by 0.6-1.9%, representing a potential increase of about a thousand applications per day for posting on the site. My analysis shows that this increase is largely driven by female job seekers being induced to apply. For example, showing this information results in an almost 6% increase in

[2] Theoretically, having a larger applicant pool will increase the expected value of the final match (Barron et al., 1985). Empirically, Van Ours and Ridder (1992) find that vacancies are filled more quickly when there is a larger applicant pool. Thus, increasing the number of applicants may result in welfare gains as long there is not too much congestion (Roth, 2008) and as long as it does not exacerbate differences in occupational choices across genders.

the likelihood a woman will finish an application, while the effect is not measurable for men. This finding is consistent with research that shows women are more ambiguity averse than men (Eckel and Grossman, 2008). Additionally, I find that the treatment increases the likelihood a female job seeker will apply to a job traditionally perceived as "male" by 0.7-1.7 percentage points. The findings from this study have both academic and policy applications. Specifically, the results suggest that providing more information can increase female applicants in industries like high tech and finance that have higher male participation rates. Overall, this paper finds that showing more information on job postings could mitigate the male-female occupation gap by exploiting gender differences in behavioral factors to increase the thickness of the female applicant pool.

The rest of the paper proceeds as follows. Section 2 discusses the literature in more detail. Section 3 describes the field experiment. Section 4 discusses the empirical strategy and results and Section 5 concludes with suggestions for further research.

2 Literature Review

Research has shown that one reason for the gender wage gap is that men are concentrated in higher paying occupations than women. However, it is unclear how much of this occupational segregation is driven by the supply side choices of women to seek lower-paying occupations rather than demand side discrimination. Previous studies have tended to focus on the demand side factors. For example Petit (2007) and Neumark et al. (1996) manipulate the name on a resume and find that men are more likely to be called for interviews than women.[3] Similarly, Goldin and Rouse (2000) find that blind auditions increase the likelihood that a woman is hired for a position by 50%. Finally, Bohnet et al. (Forthcoming) find that female applicants are evaluated differently than male applicants. However, other studies have not found evidence of gender bias in the hiring process. For example, Kuhn and Shen (2013) find that

[3] A notable exception is Bertrand and Mullainathan (2004).

higher skilled jobs are actually less likely to show a gender preference in their job postings. In addition, large employers of high skilled workers in the US have recently explicitly stated they would like to close the gender gap in their firms.[4] Finally, a set of studies has shown that increased gender diversity in the workforce has positive results for a firm (Weber and Zulehner, 2014, 2010; Hellerstein et al., 2002). Together these studies show that although some of the occupation gender gap may be driven by demand side discrimination, this does not seem to be the full story.

Regarding supply side factors, Fernandez and Friedrich (2011) find that female job seekers state a preference for a more “female” receptionist position versus a more “male” computer programmer position. This implies that women’s underlying preferences are driving the occupation gap; thus from a policy perspective, we would need to change women’s preferences to close the gap. However, in a recent field study Flory et al. (2015) find women are less likely to apply to postings that include more “male” wording, a more competitive pay structure, or greater pay uncertainty. Gaucher et al. (2011) find a similar result in a laboratory setting. In another study Samek (2015) finds a more competitive pay scheme deters both men and women from applying, but that the effect is larger for women. With the exception of Fernandez and Friedrich (2011), supply side studies find that women are deterred from applying by the specific information in the job posting or advertised pay structure. In related work on financial disclosures, two studies find that psychological factors affect take up behavior (Bertrand and Morse, 2011; Bertrand et al., 2010). These findings imply that changing how job positions are advertised could decrease the occupation gender gap.

This paper contributes to the gender gap research by studying how the information provided to applicants impacts their decision to apply. Specifically, being shown the number of previous applicants may help a job seeker weigh the costs of application against the benefits of a possible job offer. Application

[4]For example in May 2014 Google announced that only 30% of its workforce is female, and only 17% of its “tech” workforce is female. Google also acknowledged that they would like to increase diversity in their workforce. See http://www.forbes.com/sites/jaymcgregor/2014/05/29/2-of-google-employees-are-black-and-just-30-are-women/

costs can be quite high in terms of time cost.[5] The benefits of applying are related to actually obtaining a job offer. In this study, I examine the relative importance of the following information effects to gain insight into applicant behaviors: (1) ambiguity aversion, (2) competition avoidance, and (3) herding.

Laboratory studies find that both women and men are affected by all three of these behavioral factors. These studies further find that women systematically differ in the extent to which they exhibit these behaviors (see Bertrand (2011); Croson and Gneezy (2009); Eckel and Grossman (2008) for extensive literature reviews). Most of these studies find that women are more likely to choose a piece-rate versus competitive tournament style payment scheme (Dohmen and Falk, 2011; Vandegrift and Yavas, 2009; Niederle and Vesterlund, 2007; Gneezy et al., 2003). Applying this finding to the job search process, being shown a higher number of applicants on a job posting may discourage women from applying if they prefer to avoid competition. However, it is also possible that herding toward more popular jobs may offset this reduction. Experiments on herding find that people are more likely to make the same choice they observe others making (Bougheas et al., 2013; Smith and Sørensen, 2011; Yechiam et al., 2008; Anderson and Holt, 1997). Although these studies do no break down results by gender, they suggest in general, that herding would lead to more job seekers applying to positions which are already over-subscribed even though the overall effect is welfare dis-enhancing. Finally, it is possible that ambiguity aversion dominates in the job application process. Ambiguity refers to situations in which the distribution of the random variable is unknown, whereas in contrast, risk refers to situations for which the distribution is known.[6] The job search process contains a number of random variables that determine the likelihood of an offer, the quality of the position, etc. When job

[5] See the online Appendix available at http://laurakgee.weebly.com/index.html, for survey results finding most people estimate the time cost of an application at over an hour. The survey includes 188 respondents and a snow ball sampling method.

[6] Note that ambiguity aversion can be modeled as a specific form of risk aversion following the work of Halevy and Feltkamp (2005) who show that behavior indicative of ambiguity aversion could also be explained by risk aversion over correlated risks. See the appendix for details. Women have been shown to be more risk averse than men in many lab experiments (Bertrand, 2011; Croson and Gneezy, 2009; Eckel and Grossman, 2008).

seekers receive information regarding the number of other applicants some of this ambiguity is reduced. As a result, ambiguity averse job seekers may be more likely to apply. Laboratory experiments on gambling choices find that subjects prefer options where the distribution of risks is known over gambles where the distribution is less well known (Halevy and Feltkamp, 2005; Ellsberg, 1961). Additional studies have found that women are more ambiguity averse than men over gains in non-abstract environments (Moore and Eckel, 2003; Schubert et al., 2000); such as the job application process. In the next section I elaborate on the setting for my field experiment and the experimental procedures used to test which of these effects dominates in the job search setting.

3 Field Experiment

The field experiment took place on the professional social networking website LinkedIn in March 2012. LinkedIn was launched in 2003. By April 2015, the website had 350 million members from over 200 countries.[7] LinkedIn is well known for its professional social networking functionality. However, it also acts as a job posting website. This paper concentrates on the job posting functionality of LinkedIn.

Although the population on LinkedIn is not a representative sample of the total worldwide labor force, it is particularly well-suited for a study of gender differences in the labor force. The largest industries represented on LinkedIn are "High Tech" and "Finance".[8] Industries like this tend to have lower levels of female labor force participation. For example only 32.5% of US professionals in STEM related fields (Science Technology Engineering and Mathematics) are female.[9]

[7] See https://press.linkedin.com/about-linkedin. As there are about 3.5 billion people in the worldwide labor force (https://www.cia.gov/library/publications/the-world-factbook/rankorder/2095rank.html), the LinkedIn population would represent about 10% of the total labor force.

[8] http://www.linkedinppc.com/target-by-industry-company-category/

[9] http://dpeaflcio.org/programs-publications/issue-fact-sheets/women-in-stem/

To use the job postings on LinkedIn, a member first navigates to the Jobs landing page (Figure 1) where she is shown some pre-selected job postings.[10] At this point the member can click on one of the postings listed, or can enter a term into the search bar, which will return results like those shown in Figure 2. After clicking on a posting, a member will see a full page description of the posting. In the field experiment, the treatment and control groups receive different descriptions, with the treatment group receiving information on the number of previous applicants for the posted position.

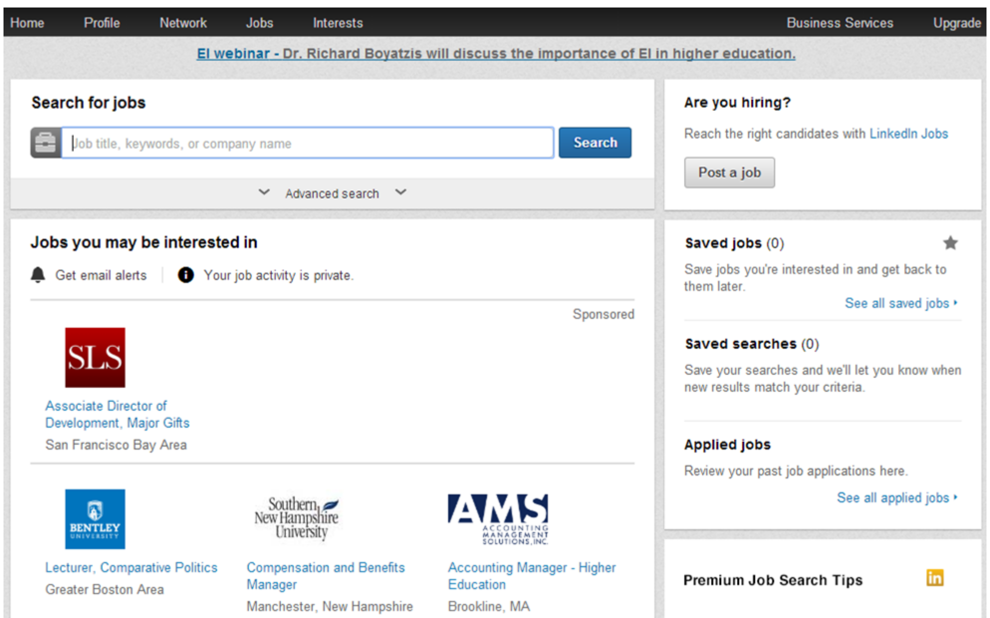


Figure 1: Jobs Landing Page

Note: This figure shows the Jobs landing page a LinkedIn user might see when she logs on to the website.

[10]Jobs are generally selected by LinkedIn based on information the member has listed on his/her profile like education, industry, and previous employment.

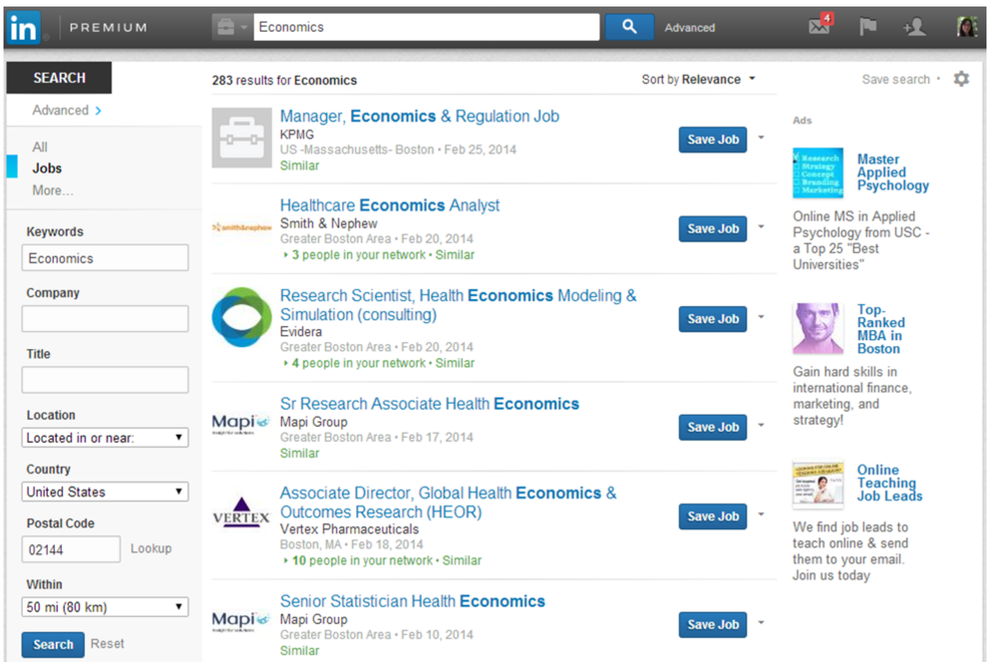
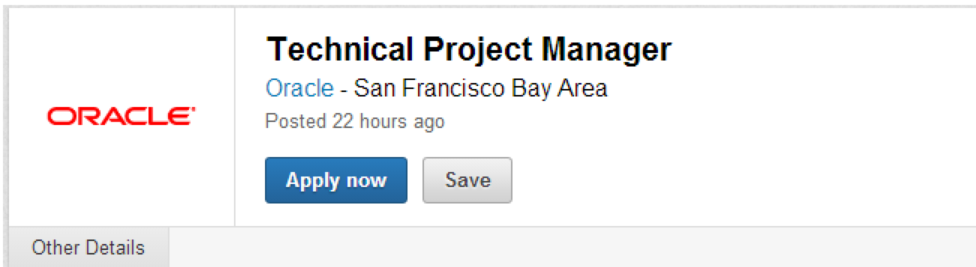
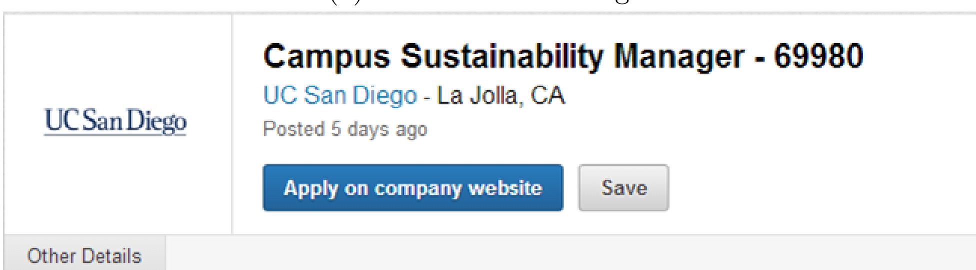


Figure 2: Job Search Landing Page

Note: This figure shows the results from a search for the term "Economics"



(a) Interior Job Posting



(b) Exterior Job Posting

Figure 3: Types of Job Postings on LinkedIn

Note: This figure shows an example of the two types of job postings on LinkedIn. Panel (a) shows an interior posting, which means that LinkedIn collects applications for a third party (Oracle). For these, I can observe if a person both begins and finishes an application. Panel (b) shows an exterior posting, which means that a person is directed to an external website to begin an application and thus I can only observe if someone begins the application. These screenshots were taken in February 2013, which is why they differ very slightly from the formatting seen in the example of the treatment vs. control screenshots in Figure 4.

LinkedIn provides two types of job postings (Figure 3). Interior postings are those where LinkedIn collects the finished application and forwards it to the company. With interior job postings, I can observe if a member both starts and finishes an application.[11] Exterior postings, on the other hand, link a job seeker to an external website. In this case I can observe only if a user starts an application.

The two main outcome variables in my experiment are the dummy variables "Start Application" and "Finish Application". For exterior postings, I can tell only if someone clicks on the "Apply" button. I cannot determine the time spent applying or even if the click was intentional. This limited information makes Start Application a noisy measure of interest in the position. By contrast, I can measure the outcome Finish Application for interior postings making it a more accurate measure of investment in applying for the job.

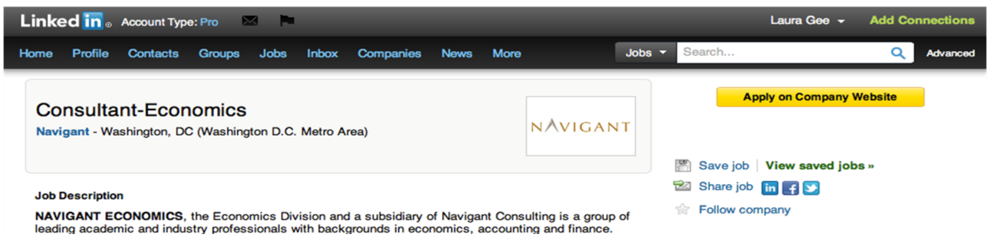
In this experiment, users were randomized into groups at the member level, so a member in the control group would see no information on any postings he visits during the 16 days of the experiment. On the other hand, a member in the treatment group looking at the same job postings would see the number of job seekers who had previously started an application as pictured in Figure 4.[12]

This design presents a unique experiment because I can observe how two people looking at the exact same posting change their behavior based on whether they know the number of other people who have already started an application. Additionally, because the information is exogenously assigned, I can rule out the possibility that those who seek out more information are already more likely to apply for a position.

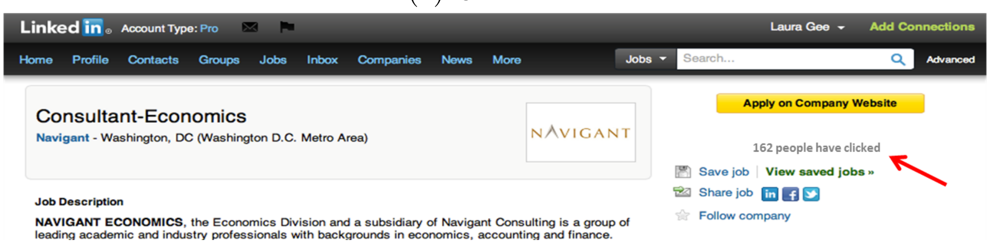
The groups were determined from the set of all active LinkedIn members

[11] I have the timestamp of when a job seeker clicks "Apply" and also the timestamp for when the user submits an application. If a person submits an application within one day of viewing the posting, then I code this as a finished application. This restriction is likely to bias the number of total finished applications downward since some people may take more than a day to finish an application or may come back at a later date to finish the application. However, I have no reason to believe this bias will be different across the control and treatment groups.

[12] For an exterior job posting, the button reads "Apply on Company Website," while for an interior job posting the button simply reads "Apply Now".



(a) Control



(b) Treatment

Figure 4: Job Posting As Seen In Control and Treatment

Note: This figure shows the way a job posting would be seen by those in the control (Panel (a)) and the treatment (Panel (b)) groups. The arrow in Panel B is to highlight the treatment for the reader, and was not shown to subjects in the experiment. The difference is those in the treatment see that "162 people have clicked" on this job posting to begin an application on the exterior website. Apart from this difference, the job posting is displayed identically to those in the control and treatment groups.

who viewed a job posting during a 16 day window in March 2012. One-fourth of these were randomly assigned to the treatment group and the remaining three-fourths were assigned to the control group.[13]

Overall, the sample includes about 2.3 million registered members from 235 countries. There are about 580,000 job seekers in the treatment and 1.7 million job seekers in the control. During the experiment, these job seekers viewed a total of over 100,000 job postings from 23 thousand companies. On average each job posting was viewed 80 times during the 16 days of the experiment and each company had about 4.7 jobs posted.[14]

3.1 Summary and Balance Statistics

The summary statistics for the subjects in the experiment are provided in Table 1. Gender is identified for 90% of the sample (57% male and 32% female).[15] For the subjects, the average age is 35, and the average year when she became a LinkedIn member is 2009. Furthermore the statistics show that 42% of the subjects are from the US, with an average of 315-316 links as of Spring 2013.[16]

[13] I exclude members who were included in a previous pilot study that took place in the two weeks before the main experiment.

[14] The minimum number of views during the 16 day period was 1 and the maximum was 6,740 with 44 being the median number of views. The minimum number of job postings from a company was 1 and the maximum was 2,568, with the median number of postings from a company being 1. Only 78 companies have 100 or more job postings up during the experiment, and the results are similar if I exclude postings from these companies in the analysis (results available from the author by request). Postings viewed by members in the control and treatment both started with an average of 17-18 previous applicants at the beginning of the experiment.

[15] Members do not provide gender, but it is imputed from their country and name (e.g. Laura in the US is coded female, and Miroslav is coded male in Slovakia). Since a large portion of the analysis concentrates on heterogeneous treatment effects by gender, a balance table by gender is provided in the online Appendix. All observable variables are similar across the control and treatment for both men and women. Also, members do not actually provide age, but it is imputed from the year the person graduated from college or high school.

[16] A “link” is a connection between two LinkedIn members that must be approved by both members. For example, a person may ask to be “linked” to a co-worker, and then that co-worker must approve that link before it appears on the website. LinkedIn keeps records of the number of connections at a company at the time of viewing, but they do not keep systematic records of the total number of links at the time of viewing.

The subjects are very well educated, with 2% listing an Associates degree, 52% listing a Bachelors, and 46% listing a post-Bachelors degree as their highest education level attained. Overall, subjects in the control and treatment groups are similar on observable variables. There is a statistically significant difference between the proportion of subjects from the US between the two groups, but the magnitude of this difference is extremely small. Finally, the statistics in Table 2 show that subjects in the control and the treatment groups view similar postings.

Table 1: Member-Level Summary Statistics

Variable	Mean (All)	N (All)	Mean (Control)	N (Control)	Mean (Treatment)	N (Treatment)	Min.	Max.	t-test for diff.
male	0.572	2,326,207	0.572	1,743,880	0.571	582,327	0	1	0.666
female	0.328	2,326,207	0.328	1,743,880	0.328	582,327	0	1	0.200
gender known	0.899	2,326,207	0.900	1,743,880	0.899	582,327	0	1	0.639
age	34.845	1,837,316	34.850	1,378,146	34.831	459,170	17	136	1.089
year membership	2008.938	2,304,683	2008.938	1,727,755	2008.939	576,928	2003	2012	0.041
US	0.419	2,326,207	0.419	1,743,880	0.418	582,327	0	1	2.233
total links (2013)	315.439	2,305,208	315.220	1,727,947	316.094	577,261	0	40,500	1.091
high school listed	0.002	1,058,647	0.002	797,023	0.002	261,624	0	1	0.408
assoc. listed	0.018	1,058,647	0.018	797023	0.018	261,624	0	1	0.183
BA listed	0.519	1,058,647	0.518	797,023	0.520	261,624	0	1	1.545
post BA listed	0.461	1,058,647	0.462	79,7023	0.460	261,624	0	1	1.562

Notes: In this table each observation is a single member. Each member occurs multiple times in the actual data set, once for each job posting the member views.

Table 2: Posting-Level Summary Statistics

Variable	Mean (All)	N (All)	Mean (Control)	N (Control)	Mean (Treatment)	N (Treatment)	Min.	Max.
start prev. apps	17.434	109,233	17.511	108,675	18.027	104,530	1	3,320
unixtime 1st seen	1332.517	109,233	1332.514	108,675	1332.502	104,530	1332	1334
firm total postings	4.726	23,115	4.727	23,107	4.756	22,926	1	2,568

Notes: "start prev. apps" is the average number of previously started applications before the experiment began. "unixtime 1st seen" is the timestamp coded into unixtime (a common measure of date used by Internet companies) when the job posting was first viewed during the experiment. Most job postings and companies are seen at least once by both the control and treatment groups. In rows 1-2 the observations are at the job posting level. In row 3, the observations are at the firm level.

4 Results

This study examines how varying the information job applicants are shown impacts their subsequent application choices. Showing job seekers the number of previous applicants may impact their choices through three possible mechanisms. First, if job seekers are ambiguity averse, showing them more information would decrease the overall ambiguity and thus increase the likelihood they will apply. Second, if job seekers avoid congested job postings, seeing a higher number of applicants would deter them from applying. Third, if job seekers herd toward more popular job postings, seeing a higher number of applicants would induce them to apply. To test which effect dominates, I make the following related set of predictions: (1) if ambiguity aversion dominates, the treatment will have a positive effect on applications, (2) if competition avoidance dominates, the treatment will have a negative effect on applications if the number shown is sufficiently high, (3) if herding dominates, the treatment will have a positive effect on applications if the number shown is sufficiently high.

There are differing welfare implications from each of these three effects. If ambiguity aversion is the dominant effect, then this could be welfare enhancing by increasing the thickness of the market and possibly decreasing the gender occupation gap. However, if instead job seekers are avoiding competition, then this could be welfare enhancing by decreasing congestion, but it could also lower the number of female applicants. Last, if the dominant effect is herding toward more popular jobs, there may be too much congestion, resulting in a welfare loss.

It is an empirical question which effect is dominant in the data. I begin by presenting the results for the overall treatment effect. I then proceed to provide the result of my tests for competition avoidance and herding by exploring the size of the treatment effect by the change in the number of applicants seen. Last, I show differential treatment effects by the type of job being applied to.

4.1 Overall Treatment Effect

Since each viewing is coded as a separate observation, I have 8,904,039 viewing/posting combinations. The outcome variables are (1) whether a person starts an application and (2) whether a person finishes an application. As explained, I can observe starting an application for both exterior and interior job postings, while I can observe finishing an application for only interior job postings. One can think of the outcome variables over two groups: those who saw an exterior posting (4,499,007 observations), and those who saw an interior posting (4,405,032 observations). The data include all the postings that a member views during the experiment, so the same member often shows up in both the Exterior and Interior sub-samples.

When a job seeker decides to apply to a job posting, she is faced with a number of unknown risks: the probability of an offer, the probability the position is a good fit, the probability of liking the corporate culture, and so on. Ambiguity aversion describes a preference for known versus unknown risks. So, for example, an ambiguity averse job seeker might prefer to apply to a job posting with a known 50% chance of an offer, rather than a posting where the odds are unknown.[17] This experiment varies the amount of information a job seeker receives and thus decreases the ambiguity and by consequence should change the behavior of ambiguity averse job seekers. In particular, I predict that it should change the behavior of female applicants because previous work has found that women are more ambiguity averse than men regarding gains in contextual environments (Moore and Eckel, 2003; Eckel and Grossman, 2008; Schubert et al., 2000). Furthermore, both Samek (2015) and Flory et al. (2015) present evidence from field experiments to show that compensation uncertainty either in the form of a tournament or an uncertain bonus, has a negative effect on women's application rates. An important distinction between this paper and the work of Samek (2015) and that of Flory et al. (2015) is that here the uncertainty is about the probability of an offer or attributes of the potential position, whereas in their studies the uncertainty is in the amount of compensation contingent on being hired. Given the findings of previous work, if ambiguity aversion is driving my results, one would expect the treatment to have a larger effect on female job seekers.

In the first three columns of Table 3, I present the results from a simple

[17] This pattern of decisions can be explained by a number of models, including max-min expected utility or bundled risky decision making (see the online Appendix for a short discussion of Ellsberg (1961); Gilboa and Schmeidler (1989); Halevy and Feltkamp (2005) and Halevy (2007)).

regression:

$$A_{i,d,j} = \beta T_i + \epsilon_{i,d,j}, \tag{1}$$

where each observation is a user i who viewed a job posting j on day d. In Panels A and B.i, the dependent variable $A_{i,d,j}$ takes the value of 1 if that user *started* that job application by clicking on the "apply" button. In Panel B.ii, the dependent variable $A_{i,d,j}$ takes the value of 1 if that user *finished* that job application by submitting all the requested materials. Note that the results in Panel B.ii indicate the unconditional likelihood of finishing an application, meaning that the dependent variable takes the value of 0 either if a person did not start the application or if the person started but did not finish the application. The reason that B.ii concentrates on the unconditional finish rate is that the randomization does not control for selection into starting an application.

Since my dependent variable takes the value of 0 or 1, a logit model would be appropriate. However, since I am most interested in the average probability of applying I use a linear probability model.[18] The independent variable T_i takes the value of one if a user is assigned to the treatment group and thus sees the number of previously started applications. All standard errors are clustered at the job posting j level.

Column 1 of Table 3 shows the results for all LinkedIn users, Column 2 shows the results for female users, and Column 3 shows the results for male users. Looking at Column 1, we can see that the treatment increases the likelihood a user will start and/or finish an application by 0.044 to 0.238 percentage points; representing a proportional increase above the control mean of between 0.855%-1.929%, representing an economically significant potential increase of over a thousand of applications per day during the 16 days of the experiment.[19] As a robustness check, I rerun the analysis with only the first

[18] A logit model yields similar results and those results are available from the author upon request.

[19] A back of the envelope calculation would be that the 2.3 million users viewed almost 9 million job postings. If they had all been in the treatment group, we would have expected an extra 16,699 applications to have been started over the 16 days of the experiment, assuming that those who apply are not substituting this application for another. This does not appear

job posting viewed and find larger effect sizes representing between a 2.124%-3.706% increase over the control (see Appendix).[20] This finding suggests there is no path dependent bias in the sequence of postings viewed.

I next compare the results for the female users in Column 2 to those of the male users in Column 3. This comparison shows the effect of the treatment is always larger for female job seekers. For example, the results in Panel B.ii indicate that the treatment increases the likelihood a female user will finish an application by 0.200 percentage points compared to an insignificant coefficient for male users of -0.033.[21] Furthermore when comparing the results in Column 2 to those in Column 3, we can see that the positive and significant effect of the treatment on starting and finishing applications is largely driven by female LinkedIn users being induced to apply.

The differences described so far may be driven by a number of factors including selection of job posting, order of viewing, and the actual number of applicants displayed. I next test these explanations using the following model:

$$A_{i,d,j} = \beta T_i + P_j + D_d + \alpha NumApply_{i,d,j} + \gamma O_{i,d,j} + \epsilon_{i,d,j}. \tag{2}$$

Note that the dependent variable $A_{i,d,j}$ still takes the value of 1 if a user decides to start or finish an application after viewing the posting. The independent variable T_i takes the value of 1 if the user was assigned to the treatment group which sees the number of previously started applications. I include a fixed effect P_j for each job posting j, so that the treatment identifies differences

to be the case, since those in the treatment start about 0.548 applications on average while those in the control start about 0.539 applications (t = 2.293). This difference in total applications is driven by a statistically significant increase for female job seekers, but a non-detectable effect of the treatment on males. Additionally, it is driven by more female job seekers being induced to apply (the extensive margin) rather than by women applying to more jobs (intensive margin), as discussed later.

[20]Since each observation is a user-job pair, users who look at many jobs, and jobs that are particularly popular have more observations in the data. One may worry that the results are being driven by these heavier users or the more popular jobs but if I weight the results so that either each user's weights sum to one or that each job posting's weights sum to one, the results are similar (see Appendix).

[21]The male and female coefficients are always statistically significantly different from each other with the exception of those in panel B.i Column 2 vs. those in Column 3.

Table 3: Likelihood of Starting/Finishing an Application

	Simple			**With Fixed Effects**		
	1	**2**	**3**	**4**	**5**	**6**
	A. Exterior: Likelihood Starting Application					
	All	**Female**	**Male**	**All**	**Female**	**Male**
Control Mean $\overline{A}_{T=0}$	12.333	11.312	12.471	12.333	11.312	12.471
Treatment β	0.238***	0.365***	0.095*	0.236***	0.409***	0.083
	(0.036)	(0.062)	(0.048)	(0.036)	(0.063)	(0.048)
Adj R2	0.000	0.000	0.000	0.040	0.044	0.039
N	4,499,007	1,477,866	2,562,137	4,499,007	1,477,866	2,562,137
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	1.929%	3.226%	0.761%	1.913%	3.615%	0.665%
	B.i Interior: Likelihood Starting Application					
	All	**Female**	**Male**	**All**	**Female**	**Male**
Control Mean $\overline{A}_{T=0}$	15.901	14.198	16.383	15.901	14.198	16.383
Treatment β	0.136***	0.107	0.046	0.102**	0.193**	-0.028
	(0.040)	(0.067)	(0.054)	(0.039)	(0.067)	(0.053)
Adj R2	0.000	0.000	-0.000	0.055	0.060	0.056
N	4,405,032	1,414,655	2,554,216	4,405,032	1,414,655	2,554,216
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	0.855%	0.753%	0.280%	0.641%	1.359%	-0.170%
	B.ii Interior: Likelihood Unconditional Finishing Application					
	All	**Female**	**Male**	**All**	**Female**	**Male**
Control Mean $\overline{A}_{T=0}$	4.422	3.681	4.740	4.422	3.681	4.740
Treatment β	0.044	0.200***	-0.033	0.030	0.208***	-0.041
	(0.023)	(0.037)	(0.031)	(0.023)	(0.038)	(0.031)
Adj R2	0.000	0.000	0.000	0.021	0.020	0.022
N	4,405,032	1,414,655	2,554,216	4,405,032	1,414,655	2,554,216
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	0.994%	5.431%	-0.696%	0.575%	5.649%	-0.864%

Notes: The dependent variable takes the value of 1 if a job seeker started or finished an application. All coefficients are multiplied by 100 for ease of reading results. Columns 1, 2 & 3 are simple models that only use the treatment as the right hand side variable. Columns 4, 5, & 6 include job posting fixed effects, days posted (omitted category 1st day) fixed effects and categorical dummies for the previous number of people who started a job application at the time of viewing (omitted category is 1-24, other bins are 25-49, 50-74, 75-99, 100-124, 125-149, 150-175, 175+). All standard errors are clustered at the job posting level. The coefficients for male vs. female job seekers are statistically significantly different from each other for all comparisons except panel B.i Column 2 vs. 3. Details of the tests are as follows: panel A ($Prob > chi2 = 0.0006$ for Column 2 vs. 3 and $Prob > chi2 = 0.0000$ for Column 5 vs. 6); panel B.i ($Prob > chi2 = 0.4819$ for Column 2 vs. 3 and $Prob > chi2 = 0.0089$ for column 5 vs. 6); panel B.ii ($Prob > chi2 = 0.0000$ for column 2 vs. 3 and $Prob > chi2 = 0.0000$ for Column 5 vs. 6) Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

in the likelihood of applying between two members viewing the exact same posting.[22] This posting fixed effect controls for time invariant attributes of a posting such as firm, industry, job description, pay range and job title. Additionally, to mitigate time trends in the raw data I use a fixed effect, D_d, for the number of days the posting has been live during the experiment. I also include the variable $O_{i,d,j}$ which controls for the order in which a job posting is seen by person i. In addition I created a set of categorical variables, $NumApply_{i,d,j}$, that divides the true number of previous applicants into eight bins: (1) 1-25, (2) 25-49, (3) 50-74, (4) 75-99, (5) 100-124, (6) 125-149, (7) 150-174 and (8) 175+. This variable controls for the true underlying number.[23]

Columns 4-6 in Table 3 present the results from this model, controlling for time invariant attributes of the job posting, the number of days the posting has been online, the order in which postings are seen, and the true number of previous applicants at the time of viewing. This analysis yields results similar to those in Column 1-3, specifically the treatment increases the likelihood a user will start or finish an application by 0.030-0.236 percentage points, representing a proportional increase above the control mean of between 0.575%-1.913%, or a potential increase of a thousand applications per day.

I next compare the results for female users in Column 5 to those for male users in Column 6. These results show that the coefficient for female job seekers is always statistically significantly larger than that for males. For example, from Panel B.ii, we see that the treatment increases the likelihood a female user will finish an application by 0.208 percentage points, compared to an insignificant coefficient for male users of -0.041.[24] Overall, the results indicate that being in the treatment group increases the likelihood a female job seeker will finish an application (Panel B.ii) by almost 6%. These results are summarized below.

[22]Only 1.4% of the job postings were seen by only a single person during the experiment so the fixed effects have a minimal effect on the effective sample size.

[23]I add this variable since LinkedIn may use this information to select which job postings to highlight for both the control and the treatment groups.

[24]The male and female coefficients in Panel B.ii are statistically significantly different from each other ($Prob > chi2 = 0.000$).

Result 1: *Showing job seekers the number of previously started applications increases the likelihood they will start or finish an application by about 0.6% to 2%; this represents a potential increase of a thousand applications per day. The increase caused by the treatment is similar with or without controls for time invariant attributes of the job posting, the number of days the posting has been online, the order in which postings are seen, or the true number of previous applicants at the time of viewing.*

Result 2: *The increase in applications due to the treatment is largely driven by female job seekers being induced to start or finish an application. The size and significance of the coefficient on the treatment is almost always larger for female vs. male job seekers. For example, being in the treatment group increases the likelihood a female job seeker will finish an application by almost 6%, whereas the effect on men is not statistically significantly different from 0.*

These results suggest that providing job seekers with the number of previous applicants may be a means of increasing the overall number of female applicants to a posting. This increase would reduce the occupation gender gap without putting an undue burden on hiring managers, as the average number of applicants for an interior (exterior) posting is 4.5 (8.4).[25]

I further explore whether the observed increase reflects new applicants (extensive margin) rather than an increase in applications from current applicants (intensive margin). For women who have submitted at least one application, women in both the control and the treatment group start an average of 1.71 exterior applications and finish an average of 2.1 interior applications.[26] This

[25]Recall that the randomization takes place at the user level, not the job posting level. Thus, each job posting appears in both the control and the treatment groups. As a result comparison of the total number of applications from the control vs. the treatment groups would not be useful.

[26]These averages are not statistically significantly different from each other for women who have submitted at least one application ($t = 0.198$ and $t = 0.493$). However, when looking at all women (including those who did not submit at least one application), then the control group starts 0.318 exterior applications and finishes 0.068 interior applications

finding shows that the number of applications on the extensive margin for women in the treatment increases, suggesting that the treatment seems to be adding to the thickness of the female applicant pool by encouraging women who would not have otherwise started an application to apply.

4.2 Treatment Effects By Number

Intuitively it seems plausible that the actual number of previous applicants seen makes a difference in how a subject responds to this information. On the one hand, if job seekers want to avoid applying to postings with greater competition, we should see a decrease in the treatment effect if the number shown is perceived as larger. On the other hand, if job seekers herd toward more popular postings, we should see an increase in the treatment effect as the number shown is perceived as larger (see the online Appendix for a short discussion of herding models (Banerjee, 1992; Anderson and Holt, 1997)).

The reason that I concentrate on the perception of the number shown (rather than the number itself) is that survey evidence finds that people viewing the exact same number may have different opinions on whether it signals high or low competition (see the online Appendix).[27] To measure perceived magnitude, I compare the number being currently viewed and the number seen previously. For example, I might compare the difference between the number of applicants seen for the 2nd job to the number of applicants seen for the 1st job.[28] The number of applicants seen for the previous posting acts as a reference point with which to compare the current posting. If the current posting applicant number is higher, then we would expect a person avoiding competition to be less likely to apply. However, if a person is herding, then

on average vs. women in the treatment group who start 0.329 exterior applications and finish 0.072 interior applications on average ($t = 3.179$ and $t = 2.03$).

[27] As a robustness check I have rerun the analysis using the absolute rather than relative number for the first job posting seen during the experiment. The results are available in the Appendix.

[28] For example, imagine Laura looks at two job postings, and the 1st posting has 10 applicants while the second has 20; here 20 is perceived as a higher number because $20 > 10$. However, if Dan looks at two job postings, and the 1st has 30 applicants while the second has 20, then 20 is perceived as a lower number since $20 < 30$.

a higher current posting applicant number should increase her likelihood of applying. It is likely that both types of individuals exist in the data, but from the perspective of a hiring manager or policymaker it is important to figure out which effect dominates and how it affects the size and composition of the applicant pool.[29]

To test if the magnitude of the treatment effect changes with the number of applicants shown, I use the following model:

$$\begin{aligned} A_{i,d,j_{order=t+1}} &= \beta T_i \\ +\lambda T_i * DIFFAPP_{i,d,j_{order=t+1}-j_{order=t}} &+ \alpha DIFFAPP_{i,d,j_{order=t+1}-j_{order=t}} \\ +P_{j_{order=t+1}} + D_d &+ \gamma O_{i,d,j_{order=t+1}} + \epsilon_{i,d,j_{order=t+1}}. \end{aligned} \quad (3)$$

Note that the dependent variable $A_{ijd,order=t+1}$ takes the value of 1 if a user decides to start or finish an application for the posting seen in order $t+1$. Thus, this analysis excludes the first posting seen. The independent variable T_i takes the value of 1 if a user is assigned to the treatment group. The treatment dummy T_i is interacted with a categorical variable $DIFFAPP_{i,d,j_{order=t+1}-j_{order=t}}$ that represents the difference between the number of applicants for the previous posting and the number for the current posting. Specifically it is a set of categorical variables with the following sixteen bins based on the difference between the number of applicants for the posting being viewed now ($order = t+1$) and the number for the posting last viewed ($order = t$): (1) -176 or lower, (2) -175 to -151, (3) -150 to -126, ... (14) 125-149, (15) 150-174, (16) 175+. The model includes job posting fixed effects $P_{j_{order=t+1}}$ to control for time invariant attributes of the job posting, as well as days posted fixed effects, D_d. In the model, combination of the coefficients β and λ represents the effect of the treatment while holding constant the effect of the job posting and the effect of the numerical difference as measured by

[29] Because the treatment is at the individual level I cannot control for whether a person is a competition avoiding type, or a herding type. Varying the treatment within individuals might address this issue but would likely yield results that would be difficult to interpret.

its bin.

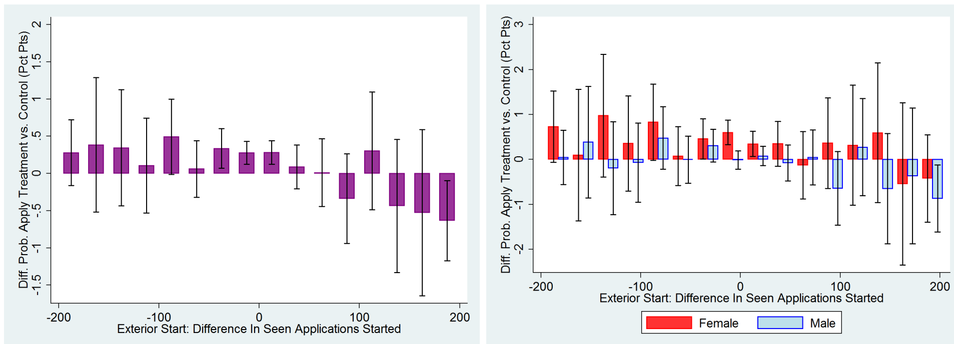
Figure 5 graphically represents the results from this model. On the vertical axis of Figure 5 is the percentage point difference in the likelihood of applying between the treatment and the control groups. On the horizontal axis is the difference in the number of applicants shown in the treatment. The error bars show the 95% confidence interval around each predicted difference. If competition avoidance is the dominating effect, one would expect a downward sloping trend in the panels of Figure 5. On the other hand, if herding is the dominating effect, one would expect to see an upward sloping trend in the panels of Figure 5.[30]

Continuing with the Figure, the top left-hand graph shows the change in the effectiveness of the treatment based on the relative number of applicants shown for all users who view an exterior job posting. The first bar on the far left shows that the treatment increases the likelihood of applying by about 0.25 percentage points above the control group when the job posting being currently viewed ($order = t + 1$) has at least 176 fewer applicants than the job posting the user last viewed ($order = t$). The second bar shows that the treatment increases the likelihood of applying by 0.30 percentage points when a user sees between -175 to -149 fewer applicants than viewed for the previous posting. Neither single point estimate is significantly different from 0.

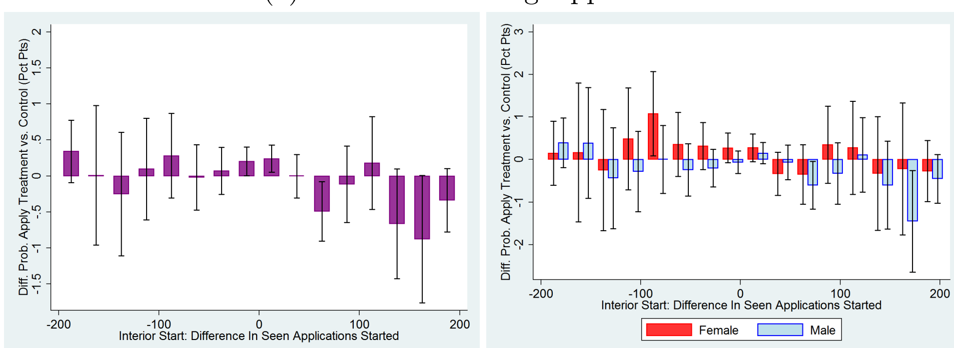
Overall, the bars in Figure 5 do not illustrate either a strong upward or downward trend as the relative number of applicants shown increases, especially when we consider the noise in our estimates. This noise in the estimates increases as the difference becomes more extreme (either positive or negative). However, this increase may reflect the lower number of observations where users see differences of more or fewer than 100 applicants.[31]

[30] To test whether viewing order creates path dependence, I also analyze the data from only the first job posting viewed. Here, the dependent variable is whether a person applies to the first job posting viewed as a function of the number of current applicants to that first job posting. The results from this analysis do not exhibit a strong pattern of competition avoidance or herding (see the Appendix.

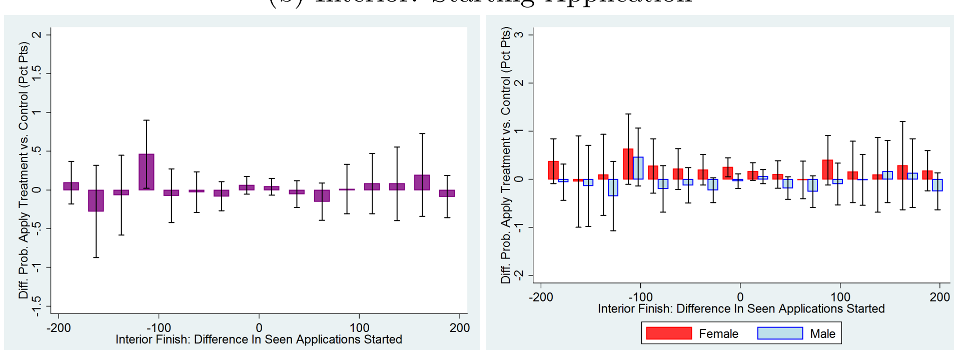
[31] There are actually a large number of observations in each bin. The bin with the fewest observations is 150 to 174 applicants with $N = 24,880$ for an exterior posting and -175 to -151 for interior postings where $N = 32,764$ for an interior posting. Although the bars



(a) Exterior: Starting Application



(b) Interior: Starting Application



(c) Interior: Finishing Application

Figure 5: Plots of Coefficients on Treatment Dummy Variable By Difference in Number Applicants Shown

In Figure 5, the top right-hand graph shows the change in the effectiveness of the treatment based on the relative number of applicants shown for female vs. male users who view an exterior job posting. Again, the bars show no strong upward or downward pattern as the relative number shown increases. I find similar results for those starting and finishing an application for an interior job posting (panels (b) and (c), respectively). Recall that competition avoidance would suggest a downward trend while herding would suggest an upward trend as the relative applicant number increases. My finding of no trend could mean that neither effect is present, that the two effects balance each other out, or that my measure does not capture how each individual interprets the number she sees. It is beyond the scope of this study to determine which is the correct interpretation of these results. However, since both competition avoidance and herding may be welfare dis-enhancing, the lack of evidence for these behaviors lends encouragement that the treatment causes no harm.

To gain further insight into the findings in June 2014, I administered an online survey (details available from author upon request). The survey has 188 respondents who were recruited using snowball sampling. This survey presents respondents with a hypothetical scenario to understand how job seekers interpret the number of previous applicants. The survey shows that 50% of respondents use the information to avoid competition, 22% to herd toward more popular jobs, and 27% to avoid ambiguity. While the majority of respondents indicate they use the information to avoid competition, they differ in what number constitutes high competition. Respondents indicate they are more likely to advance to the next stage of the interview process if there are 10 previous applicants versus 100 previous applicants. They also indicated they believe they are more likely to enjoy the position if there are 100 versus 10 previous applicants. These survey results, combined with findings regarding

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do not suggest a linear model, I ran one with the treatment and the interaction of the treatment with the raw difference (available upon request), and I find that the interaction with the treatment is always insignificant with two exceptions: (1) the full group and (2) men starting an external application. Even in these cases, the coefficient is quite small, implying a one unit increase in the difference seen results in a -0.001 percentage point decrease in the likelihood of application.

treatment effect changes by difference in number seen, lead me to Result 3.

***Result 3**: There is no strong evidence that either competition avoidance or herding is the dominant effect from showing a job seeker the number of previous applicants for either male or female job seekers.*

4.3 Treatment Effect By Job Type

Thus far, we have seen that showing the number of previous applicants increases the likelihood of a job seeker starting or finishing an application, and that this increase is larger for female job seekers than male job seekers. These findings have implications for firms actively seeking more female applicants. If a firm is interested in increasing the pool of female applicants it is important to know if the treatment is simply increasing the number of female applicants for "female jobs" or if it raises the likelihood women will apply to traditionally perceived "male" jobs.

For the purposes of this study a "male job," $M_{i,d,j}$, is defined as a job where over 80% of those who start an application in the control group are male. $M_{i,d,j}$ is defined for only those jobs which have at least one person who starts an application in the control group. Consequently, I restrict the sample in this analysis to those jobs with at least one male or female user who starts an application for the job posting in both the treatment and control groups.[32] I use $M_{i,d,j}$ as the dependent variable to test if the treatment increases female applications for these "male" positions. The model is shown below:

$$M_{i,d,j} = \beta T_i + P_j + D_d + \alpha NumApply_{i,d,j} + \gamma O_{i,d,j} + \epsilon_{i,d,j}. \quad (4)$$

Table 4 reports the results from this model. The results in Column 1 of Table 4 show that overall the treatment has a positive effect on the likelihood

[32] This definition is for the outcome variable of *starting* an application. For *finishing* an application, I define $M_{i,d,j}$ as a job with at least 80% males among those who finish the application. In this case, I restrict the sample to those jobs with at least one male or female user who finishes the application in the control and treatment groups.

that any person (male or female) will apply to a "male job." Furthermore, the results in Columns 2 and 3 show that this effect is largely driven by an increase in the likelihood of female applicants applying to "male jobs." This finding provides further evidence of the effectiveness of the treatment in increasing the number of female applicants in industries which are actively seeking to diversify their workforce, and leads to Result 4.[33]

Result 4: *The treatment increases the number of female applicants to "male jobs."*

[33]The proportional gains for the treatment group are also quite large (e.g. a 1.180 percentage point increase from a mean of 1.197 for female users in Panel A), but this is largely driven by the definition of the outcome variable as a job with greater than 80% male applicants in the control group.

Table 4: Likelihood of Applying to a "Male" Job

	With Fixed Effects		
	1	**2**	**3**
A. Exterior: Likelihood Start App			
	All	**Female**	**Male**
Control Mean $\overline{M}_{T=0}$	4.295	1.197	6.0216
Treatment β	0.606***	1.180***	0.340***
	(0.025)	(0.035)	(0.038)
Adj R2	0.129	0.111	0.124
N	3,004,335	1,024,128	1,686,593
B.i Interior: Likelihood Start App			
	All	**Female**	**Male**
Control Mean $\overline{M}_{T=0}$	5.944	1.798	8.148
Treatment β	0.419***	1.026***	0.112**
Adj R2	0.156	0.140	0.148
N	3,508,031	1,153,665	2,016,025
B.ii Interior: Likelihood Finish App			
	All	**Female**	**Male**
Control Mean $\overline{M}_{T=0}$	2.445	0.668	3.426
Treatment β	0.395***	0.741***	0.267***
	(0.025)	(0.034)	(0.038)
Adj R2	0.058	0.054	0.056
N	2,009,987	660,717	1,155,056

Notes: The dependent variable takes the value of 1 if a job seeker started or finished an application to a "male" job. A position is a "male" job if over 80% of the applicants in the control group are male. All the female coefficients are statistically significantly different from the male coefficients (Panel A $Prob > chi2 = 0.0000$; Panel B.i $Prob > chi2 = 0.0000$; Panel B.ii $Prob > chi2 = 0.0000$). All coefficients are multiplied by 100 for ease of reading results. The results include job posting fixed effects, days posted (omitted category 1st day) fixed effects and categorical dummies for the previous number of people who started a job application at time of viewing (omitted category is 1-24, other bins are 25-49, 50-74, 75-99, 100-124, 125-149, 150-175, 175+). All standard errors are clustered at the job posting level. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5 Conclusion

This paper uses LinkedIn to conduct a large scale field experiment with about 2.3 million real world job seekers. The results of this experiment show that providing information about the number of previous applicants causes more people to apply to a job posting and that this effect is greater for female applicants. These findings are especially relevant for firms looking to increase the number of female applicants. In short, this paper illustrates a low cost, light touch intervention to reduce the occupation gender gap.

Specifically I find that showing a job seeker the number of previous applicants for a job posting increases the likelihood of application by 0.6-1.9%. Since millions of job seekers view job postings each week on websites like LinkedIn, this translates to an increase in the number of applications of at least a thousand per day.

I also find that the relative number of previous applicants shown does not lead to an increase or decrease in the applications when the relative number shown is high. I interpret this finding as evidence that the dominant effect applicants exhibit is neither competition avoidance nor herding behavior. I thus conclude that the overall positive treatment effect can be explained by models of ambiguity aversion, especially the larger effect observed for female job seekers. Overall, the results indicate that this intervention should not be welfare dis-enhancing since it increases the thickness of the female applicant pool to jobs that particularly need more female applicants.

This paper has focused on the short-term effects of providing applicants with more information during the application process. Research about the long-term effects of providing more information on both unemployment duration and job tenure is an important avenue for future research.

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6 Appendix (For Online Publication)

6.1 Survey

In June 2014 I administered an online survey to obtain insight into how job applicants perceive the number of previous applicants. I used a snowball sampling technique and ended up with $N = 188$ respondents. Of those, 96 had a LinkedIn profile and would consider using LinkedIn to apply for a job. Of this group 51% said that it takes them over an hour to apply for a job, 36% said it takes 31-60 minutes, and the remaining 12% said it takes 5 to 30 minutes.

Survey respondents were shown two almost identical job postings as pictured in Figure 6. The "BLUE" posting has no information and is the same as the control in the field experiment. The "PURPLE" shows the number of previously started applications; this number was randomly assigned to be 2, 26, 72, 273 or 4124 for each survey respondent. Survey respondents were asked "If you were going to apply to either Posting BLUE or Posting PURPLE below, which posting would you prefer to apply to?". Excluding those who could not tell the difference between the BLUE and PURPLE posting, or who thought that the lack of information on the BLUE posting meant 0 applications (N=92), 45% preferred the treatment (PURPLE) to the control (BLUE). For female respondents 45% preferred the treatment compared to only 44% of the male respondents, but the difference is not statistically significant.

The main purpose of this survey was to determine how people's beliefs about applying to a job were affected by viewing the number of previously started applications. After making the choice between the BLUE and PURPLE posting, respondents were asked "In your own words please explain why you chose the BLUE or PURPLE posting?" The responses fell into four broad categories: (1) those who dislike ambiguity by a preference for more information, (2) those who prefer to avoid congestion/competition, (3) those who herd toward more popular job postings and (4) other.[34] A research assistant was able to categorize 74 of the responses into one of the three non-other categories. Interestingly the respondents seem to interpret the same number (e.g. 2, 26 etc) differently. For example, some believe that seeing 2 previous applicants means there is low congestion/competition, while others think this is high. The fact that people view the same number many ways may explain why there is no pattern of herding/congestion in the field study. This difference in perception can be seen in Figure 7, which shows the proportion of respondents that interpreted the number shown as a sign of congestion/competition,

[34] "Other" includes responses that comment on aesthetic appearance, or are vague.

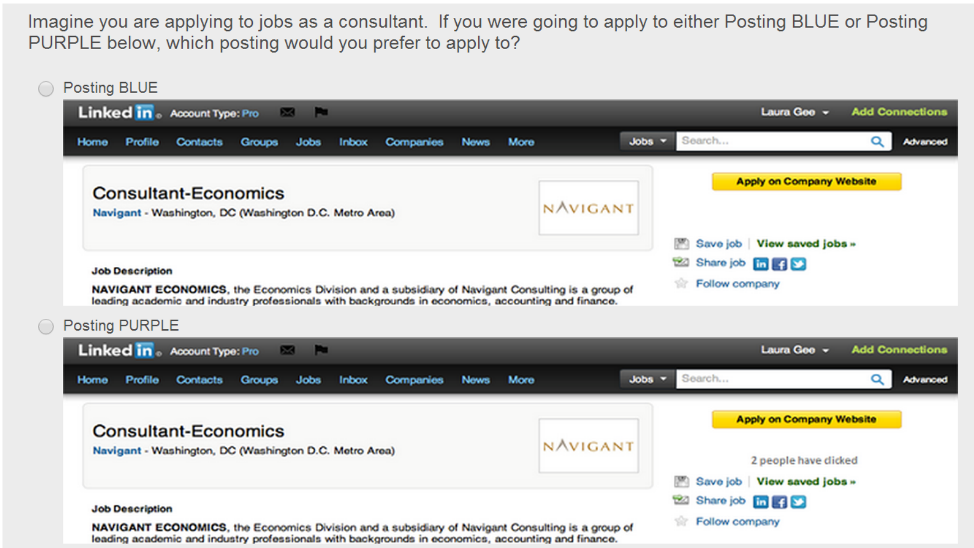


Figure 6: Type of Response by Number Seen

Note: This is the survey question that respondents answered. The number shown was randomly assigned to be either 2, 26, 72, 273 or 4124.

signalling quality, or as extra useful information. Figure 7 shows that every number seen has a variety of interpretations, with the exception being 4124, which the vast majority interpreted as a signal of congestion/competition.

Here are a few examples of each type of response:

1. Like Information

   - I'd rather have the information to guide both how much time I invest in customizing my resume/ linkedin profile / cover letter and to set my expectations (Female / Shown 4,124)
   - I figure more information is better. Given that I know they CAN post the number of clicks, it feels deceptive to hide that information. (Male / Shown 72)

2. Avoid Congestion/Competition

   - If over 4000 people have applied to a job posting, I would be unlikely to get the job. Therefore, it isn't worth the time to apply. (Male / Shown 4124)
   - When I saw that two people had already clicked on the posting of the purple it made me feel very anxious. I guess that I like to think

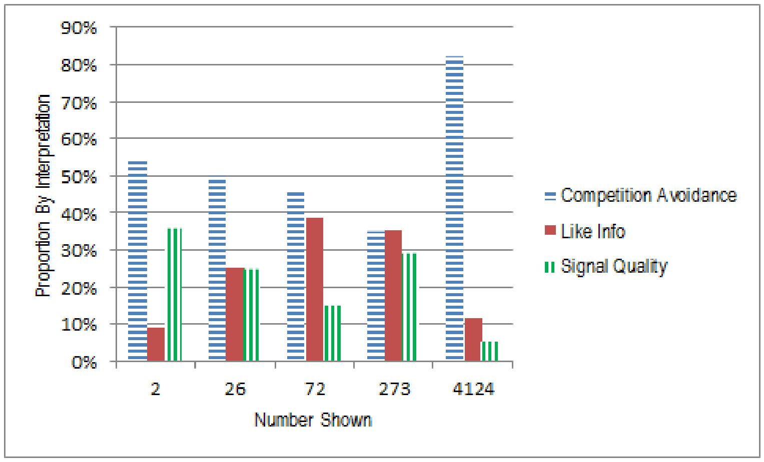


Figure 7: Jobs Landing Page

Note: This figure shows the proportion of respondents who interpreted the number of previously applicants as either (1) giving information about competition or congestion, (2) giving information allowing them to herd toward more popular postings or (3) having more information in general. The proportion is shown for each number of previously started applications either 2, 26, 72, 273 or 4124. For example for those who saw the number 26, 43% felt this signalled competition, 21% felt it signalled popularity, and 36% liked the additional information.

that I am the only person who is applying and therefore I have a high probability of getting the position. (Female / Shown 2)

3. Herd Toward Popular

   - That additional piece of information helps validate my interest by showing me how desirable that position is to other job seekers. (Male / Shown 273)
   - The information on the people who have clicked on the job tells me it is a desirable job with a reputable company (Female / Shown 273)

Another goal of the survey was to determine if people felt that competition was declining as the number seen declined. Survey respondents were asked the following two questions:

- If a job posting that you applied to said 10 people had already begun that application how likely do you believe you would be to get the to the next step in the interview process and eventually get a job offer?
  - Very Unlikely (0-20%)

- Unlikely (21-40%)
- Undecided (41-60%)
- Likely (61-80%)
- Very Likely (81-100%)

- If a job posting that you applied to said 100 people had already begun that application how likely do you believe you would be to get the to the next step in the interview process and eventually get a job offer?
  - Very Unlikely (0-20%)
  - Unlikely (21-40%)
  - Undecided (41-60%)
  - Likely (61-80%)
  - Very Likely (81-100%)

The results from the 137 respondents who answered both questions are represented in Figure 8. The distribution is concentrated around "Very Likely" and "Likely" when only 10 previous applicants are seen, but shifts toward the "Unlikely" and "Very Unlikely" when 100 previous applicants are seen. This result implies that, as subjects see higher relative numbers, they believe they face greater competition. This it supports the use of the relative difference in number seen to test for competition aversion. The shift in the distribution is similar for female and male respondents.

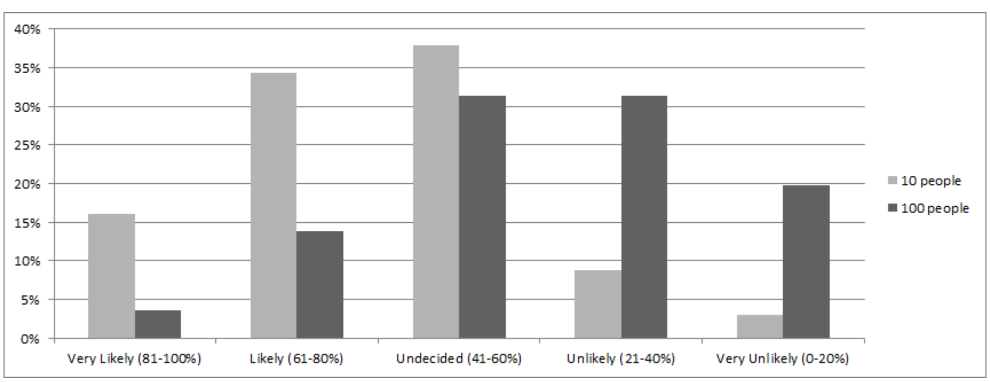


Figure 8: Likelihood of Job Offer

Note: This figure shows the proportion of respondents who said they believed they were likely to go on to the next step of the interview process and eventually get a job offer if they saw 10 vs. 100 previous applicants.

A final goal of the survey was to determine if people felt that the quality of the position was increasing as the number seen increased. Survey respondents were asked the following two questions:

- If a job posting that you applied to said 10 people had already begun that application how likely do you believe you would like that job?
  - Very Unlikely to like job (0-20%)
  - Unlikely to like job (21-40%)
  - Undecided on if will like job (41-60%)
  - Likely to like job (61-80%)
  - Very likely to like job (81-100%)
- If a job posting that you applied to said 100 people had already begun that application how likely do you believe you would like that job?
  - Very Unlikely to like job (0-20%)
  - Unlikely to like job (21-40%)
  - Undecided on if will like job (41-60%)
  - Likely to like job (61-80%)
  - Very likely to like job (81-100%)

The results from the 137 respondents who answered both questions are represented in Figure 9. The proportion reporting they are "Very Likely" or "Likely" to enjoy the job is larger when 100 previous applicants are seen rather than 10. This shift in the distribution is not very large, but it implies that individuals do believe there is a positive quality signal as the number of previous applicants shown rises. The shift in the distribution is similar for female and male respondents.

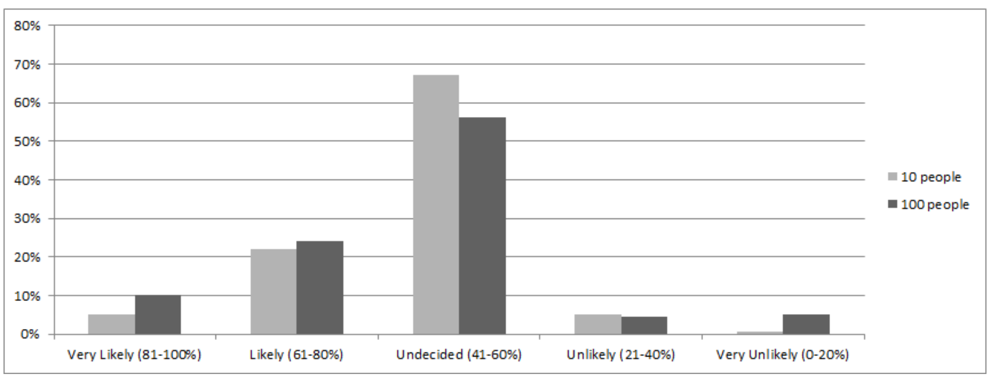


Figure 9: Likelihood of Liking Job

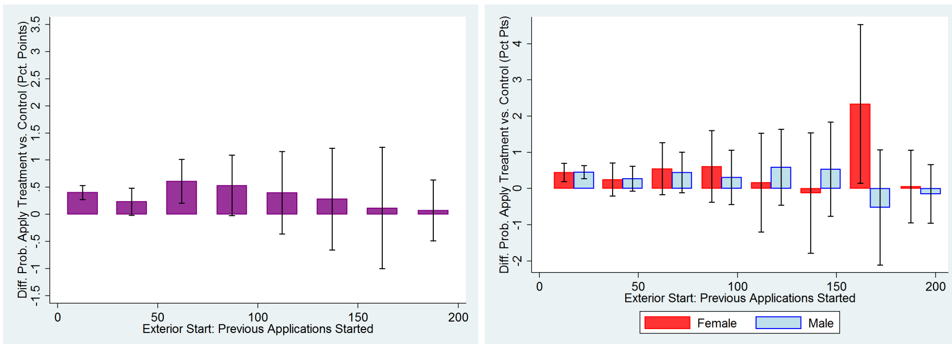
Note: This Figure shows the proportion of respondents who said they believed they were likely to "like" a job if they saw 10 vs. 100 previous applicants.

6.2 Results For Only First Job Seen

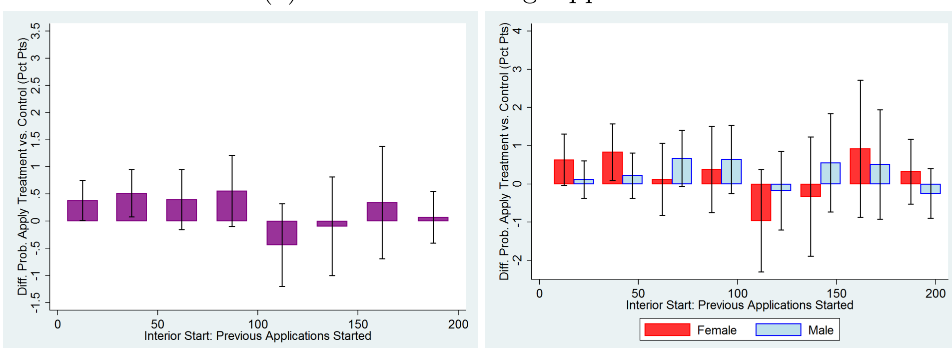
Table 5: First Job Seen: Likelihood of Starting/Finishing An Application

	Simple			With Fixed Effects		
	1	**2**	**3**	**4**	**5**	**6**
	A. Exterior: Likelihood Starting Application					
	All	**Female**	**Male**	**All**	**Female**	**Male**
Control Mean $\overline{A}_{T=0}$	9.623	9.022	9.580	9.623	9.022	9.580
Treatment β	0.355***	0.390***	0.351***	0.349***	0.411***	0.356***
	(0.064)	(0.109)	(0.085)	(0.067)	(0.122)	(0.091)
Adj R2	0.000	0.000	0.000	0.049	0.050	0.051
N	1,134,109	375,568	644,449	1,134,109	375,568	644,449
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	3.688%	4.322%	3.890%	3.626%	4.555%	3.945%
	B.i Interior: Likelihood Starting Application					
	All	**Female**	**Male**	**All**	**Female**	**Male**
Control Mean $\overline{A}_{T=0}$	10.589	9.931	10.599	10.589	9.931	10.599
Treatment β	0.225***	0.290**	0.157	0.208**	0.303*	0.121
	(0.065)	(0.111)	(0.086)	(0.065)	(0.120)	(0.090)
Adj r2	0.000	0.000	0.000	0.052	0.044	0.051
N	1,192,098	387,280	685,050	1,192,098	387,280	685,050
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	2.124%	2.919%	1.481%	1.964%	3.050%	1.141%
	B.ii Interior: Likelihood Finishing Application					
	All	**Female**	**Male**	**All**	**Female**	**Male**
Control Mean $\overline{A}_{T=0}$	2.536	2.225	2.674	2.536	2.225	2.674
Treatment β	0.094**	0.207***	0.047	0.089**	0.223***	0.039
	(0.033)	(0.055)	(0.045)	(0.034)	(0.062)	(0.047)
Adj R2	0.000	0.000	0.000	0.013	-0.007	0.008
N	1,192,098	387,280	685,050	1,192,098	387,280	685,050
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	3.706%	9.303%	1.757%	3.508%	10.022%	1.458%

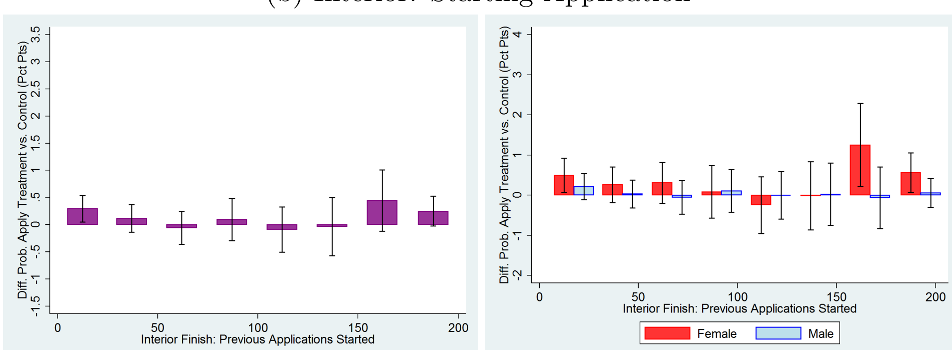
Notes: The dependent variable takes the value 1 if a job seeker started or finished an application. All coefficients are multiplied by 100 for ease of reading results. Columns 1, 2 & 3 are simple models that use only the treatment as the right side variable. Columns 4, 5, & 6 include job posting fixed effects, days posted (omitted category 1st day) fixed effects and categorical dummies for the previous number of people who started a job application at the time of viewing (omitted category is 1-24, other bins are 25-49, 50-74, 75-99, 100-124, 125-149, 150-175, 175+). All standard errors are clustered at the job posting level. The coefficients for male vs. female job seekers are not statistically significantly different from each other for all comparisons except panel B.ii; panel A ($Prob > chi2 = 0.7789$ for column 2 vs. 3 and $Prob > chi2 = 0.7022$ for column 5 vs. 6); panel B.i ($Prob > chi2 = 0.3441$ for column 2 vs. 3 and $Prob > chi2 = 0.2063$ for column 5 vs. 6); panel B.ii ($Prob > chi2 = 0.0251$ for column 2 vs. 3 and $Prob > chi2 = 0.0148$ for column 5 vs. 6) Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$



(a) Exterior: Starting Application



(b) Interior: Starting Application



(c) Interior: Finishing Application

Figure 10: First Job Seen: Plots of Coefficients on Treatment Dummy Variable By Number of Applicants Shown

6.3 Ambiguity Aversion

6.3.1 Ambiguity Aversion: Job Seekers of Two-Minds

The canonical example of ambiguity aversion is the Ellsberg two urn problem. In this problem, a person is shown a "Risky Urn" with 50 red balls and 50 black balls, and an "Ambiguous Urn" with an unknown number of red and black balls. The person then decides whether to place a bet on a red or black ball being drawn from either urn. Subjects tend to be be indifferent between a bet on red or black in the "Risky Urn," but have a lower willingness to pay for a bet on the "Ambiguous Urn" (Ellsberg, 1961). This pattern of choices is an illustration of ambiguity aversion.

Applying the logic of Ellsberg (1961) to our setting, a job seeker wins a prize for correctly identifying a job posting type as "good" or "bad" – this is analogous to an Ellsberg decision maker who will win \$100 by correctly identifying if a ball drawn from an urn will be red or black. For job applicants the prize of correctly identifying a good application may be the potential job, while the prize for identifying a bad application might be forgoing the loss of the time from applying.[35]

Those in the treatment group have a better idea of the probability the application is good or bad. For example, a 50% chance of good and a 50% chance of bad, is more similar to a "Risky Urn" that contains exactly 50 red balls and 50 black balls. In contrast, a person in the control group is told only that there is some chance the posting is good and some chance it is bad, like an "Ambiguous Urn" with an unknown composition of red and black balls. Ellsberg (1961) would predict that those in the treatment group will report a higher willingness to pay for a bet on either good/bad than those in the control group due to ambiguity aversion.

This a pattern of decisions can be explained by Maxmin Expected Utility (Gilboa and Schmeidler, 1989). Here, a decision maker attempts to maximize the "minimum expected utility" from all possible priors. In the treatment group, the minimum expected utility of a bet on good/bad is a 50% chance of the prize;, thus it is non-zero. In other words, the Ellsberg "Risky Urn" has a minimum expected utility of \$50 ($EU = .5(100) + .5(0) = 50$) for a bet on either red or black. By contrast, a job seeker in the control group takes the conservative view that if she bets on good there may be a 0% chance the job is

[35] In the Ellsberg two urn example the prize for correctly identifying red or black is the same, whereas in the job application the prize for identifying a good or bad application may differ. Furthermore, the size of the prize itself may be unknown in the job application example. For clarity, I use the canonical Ellsberg example to motivate how ambiguity aversion would apply to our setting even though it is not perfectly analogous.

good, and if she bets on bad there may be a 0% chance the job is bad. She has a non-unique prior that there are zero red balls when she bets red, and there are zero black balls when she bets black. In this case the minimum expected utility is zero for both priors. Individuals with Maxmin Expected Utility will report a higher willingness to pay for a bet on good or bad in the treatment group than in the control. This shows that my results are consistent with the prediction of Maxmin Expected Utility.

6.3.2 Risk Aversion: Job Seekers of One-Mind

Maxmin Expected Utility requires a job seeker to simultaneously believe a job posting has a zero chance of being both good and bad. By contrast, Halevy and Feltkamp (2005) offer a model that explains the classic Ellsberg two urn problem by assuming that decision makers are risk averse and they view each decision as a bundle of decisions with correlated risks and outcomes.

For example, a job seeker might view the decision to apply as a bet on identifying if job 1 is good/bad and a bet on identifying if job 2 is also good/bad. Furthermore, the likelihood of correctly identifying the job type for job 1 is positively correlated with correctly identifying job 2 as good/bad. This is a plausible assumption, since applicants may be generally strong (or weak) candidates for many similar jobs.

To apply the intuition of Halevy and Feltkamp (2005) to this experiment, I present a simple example. Suppose subjects in the treatment group face two job postings with identical chances of correctly identifying the jobs' types as good/bad. Here the number of previous applicants (N) gives the job seeker information about the probability of winning a prize for correct identification. The probability of winning is $p = 1/N$, since there is more competition as N rises. Also the quality of the prize is increasing as N increases, let us assume $q = N$.

If a person in the treatment group observes two previous applicants $N = 2$, then $p = 0.5$ and $q = 2$ for job 1 and job 2. The probability she correctly identifies both job 1 and job 2 is $p^2 = .25$, the probability she identifies only one correctly is $2p(1-p) = .5$ and the probability she incorrectly identifies both is $(1-p)^2 = 0.25$. Let us assume the prize for correctly identifying both jobs is $2q$ =4 utils, one is 2 utils, and none is 0 utils.

If that same person in the control group did not observe N, then we assume she has a uniform prior over all the possible probabilities and prizes. This means there is a 1/3 chance respectively of correctly identifying both jobs, or neither.[36] Again, the prize for correctly identifying both is 4 utils, one is 2

[36] Think of the uniform prior as being faced with an urn with 100 balls some are black and

utils, and none is 0 utils. If this person is risk-neutral (RN) with $U = x$ then the expected utility is the same in both the treatment or control. However if the person exhibit risk aversion (RA) with $U = \frac{x^{0.5}}{0.5}$, then the expected utility is higher in the treatment than in the control.[37]

Applying the Halevy and Feltkamp (2005) model to the job application context, if job seekers view the decision to apply to a single job as part of a bundle of decisions with correlated outcomes, then they may have a single prior, but will still be more likely to apply in the treatment than in the control.

6.4 Herding

In the classic herding example, a group is shown one Black urn and one Red urn each with a 50% chance of being the urn in use (Anderson and Holt, 1997). Everyone who correctly guesses which urn is in use will get a prize. We can apply this game to our setting by supposing that all the job seekers win a prize if they correctly identify a job posting as high quality. Therefore worth the time spent applying. Specifically the herding example includes a Black Urn with one red and two black balls, and a Red Urn with two red

some are red. And they want to know the chance that a bet on a red ball will be correct. A person with no information believes there is the same chance of 0 red, 1 red, 2 red up to 100 red balls in the urn. So the chance of getting two red balls is:

$$\sum_{i=0}^{100} \frac{1}{101}(\frac{i}{100})^2 = \frac{1}{3} \tag{5}$$

The chance of getting none is:

$$\sum_{i=0}^{100} \frac{1}{101}(1 - \frac{i}{100})^2 \cong \int_0^1 p^2 dp = \frac{1}{3} \tag{6}$$

[37]Risk Neutral

$$Treatment : EU_{RN} = \frac{1}{4} * 4 + \frac{1}{2} * 2 + \frac{1}{4} * 0 = 2 \tag{7}$$

$$Control : EU_{RN} = \frac{1}{3} * 4 + \frac{1}{3} * 2 + \frac{1}{3} * 0 = 2 \tag{8}$$

Risk Averse

$$Treatment : EU_{RA} = \frac{1}{4} * \frac{4^{0.5}}{0.5} + \frac{1}{2} * \frac{2^{0.5}}{0.5} + \frac{1}{4} * \frac{0^{0.5}}{0.5} = 2.41 \tag{9}$$

$$Control : EU_{RA} = \frac{1}{3} * \frac{4^{0.5}}{0.5} + \frac{1}{3} * \frac{2^{0.5}}{0.5} + \frac{1}{3} * \frac{0^{0.5}}{0.5} = 2.27 \tag{10}$$

balls and one black ball. Each person observes a private draw of one ball from the chosen urn (with replacement) and gets to make a public choice that the urn is either Red or Black. The starting prior is therefore a 50% chance of the Black Urn. If the first person privately draws a black ball, his posterior probability of correctly identifying the Black Urn is two-thirds, so he publicly bets on the Black Urn.[38] If the second person privately draws a black ball, then her posterior probability of correctly identifying the Black Urn is four-fifths and she publicly bets on the Black Urn.[39] At this point, if the third person privately draws a red ball, he will ignore his private signal and bet on the Black Urn because his posterior will be two-thirds.[40] Now, all future choices will be a bet on the Black Urn regardless of each person's private signal. In other words, an information cascade has begun and there is herding on the choice of Black.

Applying this herding model to the job application context, each job seeker must decide whether to apply (bet on the Black Urn) or not apply (bet on Red Urn). If herding is driving our positive finding, then after a threshold number of previous applicants, all future job seekers should choose to apply and the likelihood of job application should rise toward 100%.

Note that the classic urn example may not be completely relevant in our setting. In the two urn example all players win a prize if they correctly identify the urn as Black or Red. However, our job seekers may perceived a high number of applicants as either a positive or negative signal depending on whether it signals job quality or high competition. Previous research finds that people tend to suffer from confirmation bias, and integrate positive signals more than negative signals (Eil and Rao, 2011; Babcock and Loewenstein, 1997; Bradley, 1978). Consequently, we may still expect to see herding even

[38] Using Bayes Rule, we have

$$P(BlackUrn|blackball) = \frac{P(b|B)P(B)}{P(b|B)P(B) + P(b|R)P(R)} = \frac{(\frac{2}{3})(\frac{1}{2})}{(\frac{2}{3})(\frac{1}{2}) + (\frac{1}{3})(\frac{1}{2})} = \frac{2}{3} \tag{11}$$

[39] Using Bayes, Rule we have

$$P(BlackUrn|blackball) = \frac{P(b|B)P(B)}{P(b|B)P(B) + P(b|R)P(R)} = \frac{(\frac{2}{3})(\frac{2}{3})}{(\frac{2}{3})(\frac{2}{3}) + (\frac{1}{3})(\frac{1}{3})} = \frac{4}{5} \tag{12}$$

[40] Using Bayes Rule, we have

$$P(BlackUrn|redball) = \frac{P(r|B)P(B)}{P(r|B)P(B) + P(r|R)P(R)} = \frac{(\frac{1}{3})(\frac{4}{5})}{(\frac{1}{3})(\frac{4}{5}) + (\frac{2}{3})(\frac{1}{5})} = \frac{2}{3} \tag{13}$$

if there is a downward effect due to increased competition.

6.5 Summary Statistics

Table 6: Summary Statistics By Gender

Variable	Mean (All)	N (All)	Mean (Control)	N (Control)	Mean (Treatment)	N (Treatment)	Min.	Max.	t-test for diff.
Male									
age	1,078,107	36.052	808,844	36.058	269,263	36.035	17	136	t = 0.949
year credit	1,329,499	2008.756	996,899	2008.756	332,600	2008.756	2003	2012	t = 0.1075
US	1,329,499	0.400	996,899	0.401	332,600	0.399	0	1	t = 1.705
links	1,320,555	345.210	990,141	344.767	330,414	346.537	0	40,500	t = 1.541
max HS	612,899	0.002	461,455	0.002	151,444	0.002	0	1	t = 1.514
max Assoc	612,899	0.017	461,455	0.017	151,444	0.017	0	1	t = 0.310
max BA	612,899	0.510	461,455	0.509	151,444	0.510	0	1	t = 0.841
max Post BA	612,899	0.471	461,455	0.471	151,444	0.471	0	1	t = 0.617
Female									
age	596,159	33.372	447,061	33.374	149,098	33.364	17	134	t = 0.359
year credit	762,848	2009.111	571,791	2009.111	191,057	2009.112	2003	2012	t = 0.083
US	762,848	0.474	571,791	0.474	191,057	0.473	0	1	t = 0.812
links	756,411	285.947	566,890	286.159	189,521	285.314	0	36,846	t = 0.690
max HS	359,470	0.001	270,568	0.001	88,902	0.002	0	1	t = 0.858
max Assoc	359,470	0.022	270,568	0.022	88,902	0.022	0	1	t = 0.814
max BA	359,470	0.550	270,568	0.550	88,902	0.551	0	1	t = 0.699
max Post BA	359,470	0.427	270,568	0.427	88,902	0.425	0	1	t = 1.008

Table 7: Underlying Models For Graphs

	Exterior Start			Interior Start			Interior Finish		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
treatment β	0.278	0.731	0.046	0.342	0.147	0.394	0.096	0.375	-0.056
	(0.225)	(0.405)	(0.309)	(0.221)	(0.385)	(0.299)	(0.140)	(0.238)	(0.192)
treat* diff -175 to -151	0.106	-0.634	0.339	-0.333	0.021	-0.004	-0.372	-0.419	-0.079
	(0.513)	(0.847)	(0.706)	(0.536)	(0.912)	(0.726)	(0.334)	(0.539)	(0.473)
treat* diff -150 to -126	0.066	0.245	-0.240	-0.594	-0.394	-0.833	-0.161	-0.281	-0.293
	(0.455)	(0.810)	(0.610)	(0.488)	(0.820)	(0.671)	(0.298)	(0.492)	(0.415)
treat* diff -125 to -101	-0.172	-0.375	-0.115	-0.245	0.343	-0.677	0.366	0.255	0.522
	(0.399)	(0.682)	(0.544)	(0.419)	(0.718)	(0.564)	(0.264)	(0.443)	(0.363)
treat* diff -100 to -76	0.214	0.098	0.431	-0.060	0.931	-0.394	-0.169	-0.098	-0.139
	(0.342)	(0.596)	(0.469)	(0.372)	(0.639)	(0.506)	(0.225)	(0.369)	(0.315)
treat* diff -75 to -51	-0.217	-0.659	-0.050	-0.361	0.213	-0.634	-0.123	-0.160	-0.065
	(0.296)	(0.521)	(0.409)	(0.320)	(0.546)	(0.431)	(0.196)	(0.322)	(0.270)
treat* diff -50 to -26	0.058	-0.274	0.260	-0.271	0.173	-0.595	-0.177	-0.174	-0.171
	(0.262)	(0.463)	(0.361)	(0.277)	(0.478)	(0.375)	(0.170)	(0.287)	(0.232)
treat* diff -25 to -1	-0.001	-0.131	-0.059	-0.139	0.130	-0.456	-0.033	-0.120	0.019
	(0.238)	(0.427)	(0.326)	(0.243)	(0.427)	(0.327)	(0.152)	(0.258)	(0.207)
treat* diff 0 to 24	0.003	-0.385	0.032	-0.101	0.132	-0.242	-0.053	-0.213	0.116
	(0.238)	(0.427)	(0.327)	(0.241)	(0.419)	(0.326)	(0.151)	(0.256)	(0.206)
treat* diff 25 to 49	-0.188	-0.383	-0.125	-0.346	-0.482	-0.459	-0.149	-0.270	-0.125
	(0.270)	(0.477)	(0.370)	(0.269)	(0.464)	(0.365)	(0.166)	(0.279)	(0.224)
treat* diff 50 to 74	-0.268	-0.861	-0.000	-0.833**	-0.494	-0.997*	-0.246	-0.386	-0.198
	(0.326)	(0.566)	(0.441)	(0.303)	(0.525)	(0.412)	(0.184)	(0.308)	(0.253)
treat* diff 75 to 99	-0.618	-0.366	-0.688	-0.456	0.201	-0.719	-0.085	0.023	-0.040
	(0.381)	(0.652)	(0.522)	(0.348)	(0.595)	(0.470)	(0.214)	(0.354)	(0.292)
treat* diff 100 to 124	0.025	-0.412	0.227	-0.163	0.132	-0.283	-0.013	-0.216	0.046
	(0.463)	(0.794)	(0.634)	(0.395)	(0.682)	(0.539)	(0.242)	(0.406)	(0.328)
treat* diff 125 to 149	-0.715	-0.136	-0.696	-1.006*	-0.474	-0.996	-0.015	-0.279	0.220
	(0.504)	(0.882)	(0.694)	(0.441)	(0.782)	(0.603)	(0.280)	(0.457)	(0.385)
treat* diff 150 to 174	-0.804	-1.276	-0.412	-1.220*	-0.364	-1.846**	0.098	-0.091	0.186
	(0.610)	(1.004)	(0.832)	(0.505)	(0.883)	(0.679)	(0.307)	(0.535)	(0.414)
treat* diff 175+	-0.913**	-1.154	-0.913	-0.680*	-0.419	-0.847*	-0.182	-0.195	-0.192
	(0.352)	(0.641)	(0.479)	(0.320)	(0.536)	(0.417)	(0.199)	(0.325)	(0.273)
diff -175 to -151	-0.589*	-0.752	-0.427	-0.208	-0.161	-0.362	0.177	0.084	0.233
	(0.263)	(0.441)	(0.360)	(0.279)	(0.463)	(0.371)	(0.173)	(0.276)	(0.241)
diff -150 to -126	-0.621**	-0.502	-0.684*	0.403	0.162	0.707*	0.212	0.246	0.342
	(0.234)	(0.400)	(0.317)	(0.246)	(0.408)	(0.336)	(0.154)	(0.245)	(0.213)
diff -125 to -101	-0.438*	-0.352	-0.416	0.051	0.492	-0.255	0.008	0.359	-0.215
	(0.206)	(0.342)	(0.283)	(0.218)	(0.365)	(0.295)	(0.132)	(0.219)	(0.183)
diff -100 to -76	-0.524**	-0.171	-0.803**	-0.107	-0.259	-0.123	0.096	0.306	-0.039
	(0.182)	(0.305)	(0.245)	(0.194)	(0.323)	(0.262)	(0.116)	(0.186)	(0.164)
diff -75 to -51	-0.492**	0.013	-0.669**	-0.153	-0.392	0.054	-0.050	0.032	-0.063
	(0.161)	(0.267)	(0.219)	(0.169)	(0.278)	(0.229)	(0.102)	(0.164)	(0.141)
diff -50 to -26	-0.660***	-0.304	-0.906***	-0.014	0.143	-0.030	0.106	0.350*	0.016
	(0.144)	(0.238)	(0.196)	(0.151)	(0.250)	(0.202)	(0.090)	(0.149)	(0.124)
diff -25 to -1	-0.769***	-0.404	-0.966***	0.030	0.040	0.050	0.161	0.273*	0.103
	(0.135)	(0.223)	(0.182)	(0.138)	(0.228)	(0.184)	(0.083)	(0.136)	(0.114)
diff 0 to 24	-0.883***	-0.520*	-1.132***	-0.057	-0.154	-0.051	0.116	0.183	0.068
	(0.135)	(0.223)	(0.182)	(0.136)	(0.224)	(0.180)	(0.082)	(0.135)	(0.112)
diff 25 to 49	-1.863***	-1.617***	-2.013***	-1.590***	-1.322***	-1.720***	-0.470***	-0.248	-0.567***
	(0.154)	(0.252)	(0.208)	(0.151)	(0.249)	(0.201)	(0.090)	(0.144)	(0.125)
diff 50 to 74	-2.528***	-2.141***	-2.793***	-2.374***	-2.293***	-2.381***	-0.785***	-0.571***	-0.872***
	(0.184)	(0.301)	(0.247)	(0.172)	(0.279)	(0.232)	(0.102)	(0.164)	(0.139)
diff 75 to 99	-3.062***	-3.161***	-3.189***	-3.033***	-2.807***	-3.168***	-1.077***	-0.843***	-1.233***
	(0.220)	(0.359)	(0.290)	(0.199)	(0.318)	(0.268)	(0.118)	(0.186)	(0.159)
diff 100 to 124	-3.708***	-3.734***	-3.639***	-3.986***	-3.519***	-4.328***	-1.410***	-1.014***	-1.711***
	(0.260)	(0.429)	(0.349)	(0.220)	(0.360)	(0.296)	(0.132)	(0.208)	(0.178)
diff 125 to 149	-3.890***	-3.780***	-4.326***	-4.157***	-3.703***	-4.311***	-1.364***	-0.902***	-1.582***
	(0.301)	(0.501)	(0.409)	(0.252)	(0.427)	(0.336)	(0.151)	(0.249)	(0.205)
diff 150 to 174	-4.125***	-3.708***	-4.216***	-4.765***	-4.847***	-4.800***	-1.805***	-1.410***	-2.008***
	(0.359)	(0.582)	(0.481)	(0.282)	(0.462)	(0.373)	(0.169)	(0.278)	(0.236)
diff 175+	-5.206***	-4.630***	-5.522***	-6.587***	-6.196***	-6.725***	-2.572***	-2.301***	-2.708***
	(0.309)	(0.473)	(0.416)	(0.230)	(0.363)	(0.301)	(0.135)	(0.216)	(0.184)
order seen	0.003***	0.061***	0.000	0.064***	0.215***	0.054***	0.016***	0.079***	0.011***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.000)	(0.002)	(0.000)
cons	14.566***	12.253***	14.991***	18.346***	14.497***	19.088***	6.110***	4.264***	6.656***
	(0.132)	(0.216)	(0.178)	(0.131)	(0.218)	(0.175)	(0.079)	(0.131)	(0.109)
Adj R2	0.039	0.043	0.038	0.053	0.058	0.055	0.021	0.019	0.022
N	3,364,898	1,102,298	1,917,688	3,212,934	1,027,375	1,869,166	3,212,934	1,027,375	1,869,166

The dependent variable takes the value of 1 if a job seeker started or finished an application. The results include job posting and days posted fixed effects. All coefficients are multiplied by 100 for ease of reading results. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 8: Main Results Weighted By User Occurrences

	Exterior Start			Interior Start			Interior Finish		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Treatment	0.331***	0.407***	0.301***	0.206***	0.218**	0.160**	0.074***	0.135***	0.038
	(0.049)	(0.085)	(0.065)	(0.046)	(0.080)	(0.062)	(0.022)	(0.038)	(0.030)
order seen	0.221***	0.232***	0.212***	0.495***	0.511***	0.472***	0.179***	0.181***	0.173***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
cons	10.149***	9.423***	10.089***	9.456***	8.607***	9.549***	2.771***	2.479***	2.923***
	(0.077)	(0.125)	(0.100)	(0.083)	(0.140)	(0.107)	(0.043)	(0.068)	(0.058)
Adj R2	0.062	0.082	0.071	0.062	0.071	0.067	0.023	0.022	0.025
N	4,499,007	1,477,866	2,562,137	4,405,032	1,414,655	2,554,216	4,405,032	1,414,655	2,554,216

The dependent variable takes the value of 1 if a job seeker started or finished an application. The results include job posting fixed effects, days posted (omitted category 1st day) fixed effects and categorical dummies for the previous number of people who started a job application at time of viewing (omitted category is 1-24, other bins 25-49, 50-74, 75-99, 100-124, 125-149, 150-175, 175+). All coefficients are multiplied by 100 for ease of reading results. Each observation is weighted by the number of times a user occurs in the data, so that each individual user contributes the same amount to these models. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 9: Main Results Weighted By Job Posting Occurrences

	Exterior Start			Interior Start			Interior Finish		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Treatment	0.263**	0.503***	0.039	0.149	0.228*	0.033	0.020	0.279***	-0.015
	(0.084)	(0.127)	(0.106)	(0.076)	(0.112)	(0.102)	(0.039)	(0.060)	(0.050)
order seen	0.001	0.073***	-0.002**	0.053***	0.223***	0.044***	0.013***	0.080***	0.009***
	(0.001)	(0.004)	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.000)
cons	16.159***	13.732***	15.895***	15.152***	11.401***	15.707***	4.606***	3.221***	4.864***
	(0.071)	(0.113)	(0.088)	(0.069)	(0.113)	(0.087)	(0.037)	(0.060)	(0.047)
Adj R2	0.163	0.277	0.187	0.078	0.128	0.098	0.050	0.097	0.071
N	4,499,007	1,477,866	2,562,137	4,405,032	1,414,655	2,554,216	4,405,032	1,414,655	2,554,216

The dependent variable takes the value of 1 if a job seeker started or finished an application. The results include job posting fixed effects, days posted (omitted category 1st day) fixed effects and categorical dummies for the previous number of people who started a job application at time of viewing (omitted category is 1-24, other bins 25-49, 50-74, 75-99, 100-124, 125-149, 150-175, 175+). All coefficients are multiplied by 100 for ease of reading results. Each observation is weighted by the number of times a job posting occurs in the data, so that each individual user contributes the same amount to these models. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 10: Results Excluding Companies with 100+ listings

	Exterior Start			Interior Start			Interior Finish		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Treatment	0.221***	0.382***	0.091	0.117**	0.193**	-0.015	0.034	0.212***	-0.039
order seen	0.008***	0.074***	0.003***	0.071***	0.238***	0.059***	0.019***	0.087***	0.013***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.000)	(0.002)	(0.000)
cons	12.341***	10.925***	12.506***	16.042***	12.922***	16.583***	5.684***	4.332***	6.065***
	(0.064)	(0.107)	(0.086)	(0.073)	(0.115)	(0.094)	(0.045)	(0.067)	(0.059)
Adj R2	0.034	0.037	0.034	0.054	0.060	0.056	0.021	0.020	0.021
N	3,200,640	1,089,583	1,812,702	4,201,370	1,361,629	2,427,339	4,201,370	1,361,629	2,427,339

The dependent variable takes the value of 1 if a job seeker started or finished an application. All coefficients are multiplied by 100 for ease of reading results. Include job posting fixed effects, days posted (omitted category 1st day) fixed effects and categorical dummies for the previous number of people who started a job application at time of viewing (omitted category is 1-24, other bins are 25-49, 50-74, 75-99, 100-124, 125-149, 150-175, 175+). Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$