The More You Know: Information Effects on Job Application Rates 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 or not a job seeker sees the number of applicants for a job posting on a large job-posting website, LinkedIn. This intervention increases the likelihood that a person will finish an application by 3.5%. Women have a larger increase in their likelihood of finishing an application than men. Overall, adding this information to a job posting may offer a light-touch way to both increase application rates and alter the diversity of the applicant pool.

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1 Introduction

Labor-market matching is important. Both firms and job seekers expend a large amount of time and money attempting to match. Understanding how job seekers decide to apply is useful. This paper presents the results from a large (over 2-million-person) field experiment run at the popular business-networking website LinkedIn. The experiment randomly varies whether a job seeker viewing a job posting sees the number of people who have clicked a button to start a job application. Both the control and the treatment group contain LinkedIn members who, collectively, are actively searching through over 100,000 job postings. Job seekers in the control and treatment conditions see identical real job postings.

I find that adding information about others' actions raises the likelihood of application by 1.9%–3.6%. That represents a potential increase of 1,500 started applications each day. There are differences in the increase from the information by observable characteristics like gender and experience, although those differences are not always statistically significant. Adding this kind of information to a job posting may offer a light-touch way to both increase applications and alter the diversity of the applicant pool.

Increasing the applicant pool can be beneficial because vacancies are filled faster when there is a larger applicant pool (Van Ours and Ridder, 1992). Firms and policy makers may want to increase workforce diversity,[1], but a firm cannot hire, for example, more female or black engineers if there is a lack of female or black applicants. Knowing how to encourage a wide range of individuals to apply could increase both the quantity and the diversity of the applicant pool.[2]

Most theoretical models assume that people rely on the most pertinent pieces of information—like the probability of an offer or the utility of the job—when they decide whether to apply.[3] But in reality job seekers may not pay attention to or have access to such information when they make their decision to apply. This paper begins to bridge between the theoretical assumptions of full information and the reality of very little information.

There is a rich history of using field experiments in labor economics. Many field experiments have explored how the demand side of the market decides who to interview by sending fictitious CVs to actual job openings.[4] Yet there are relatively few supply-side field

[1]See Weber and Zulehner (2014, 2010) and Hellerstein et al. (2002). As an example, in May 2014, Google, noting that only 30% of its overall workforce and 17% of its "tech" workforce is female, acknowledged wanting to increase the diversity of its workforce. See http://www.forbes.com/sites/jaymcgregor/2014/05/29/2-of-google-employees-are-black-and-just-30-are-women/.

[2]It is also possible that increasing the number of applicants could lead to too much congestion (Roth, 2008). I explore that topic in the Further Analysis section.

[3]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).

[4]See Deming et al. (2016); Eriksson and Rooth (2014); Kroft et al. (2013); Oreopoulos (2011); Lahey

studies. For example, Flory et al. (2015) set up an office assistant position and advertise it in 16 different cities. They find that women are less likely to apply for a job if its description includes more "male"-oriented wording, or alludes to a more competitive pay structure or greater pay uncertainty.[5] Samek (2015) advertises a temporary administrative position she created and finds that a nonprofit framing increases applications, while a more competitive pay scheme deters women from applying more than it deters men. Both Flory et al. (2015) and Samek (2015) vary the description of the position but do not offer any information about the actions of others. In contrast, Coffman et al. (2014) find that stating that 84% of applicants accept their Teach for America (TFA) offer significantly increases an applicant's likelihood of accepting the offer as well as her commitment to the teaching position.

Many of the previous labor market field experiments have rather limited generalizability because they either rely on researcher-created resumes or study only one specific type of position. In contrast, this study presents evidence about the behavior of a broad set of real professional job seekers in the context of a wide range of career-oriented job postings. Over the duration of the experiment, these job seekers view over 100,000 different job postings from over 23,000 firms. The experimental results are hence likely to be applicable across various other professional labor markets.

The current number of applicants for a job can be thought of as a piece of social information because it describes the actions of others. Showing social information can increase the likelihood that a person would engage in a variety of behaviors such as applying to college, accepting a job offer, staying at a job, donating to charity, paying taxes, taking environmentally friendly actions, and more.[6]

What separates the present study from the aforementioned experiments is that in most of the previous settings the information represents a clearly positive signal that should increase a person's likelihood to engage in the desired action. For example, the information that 84% of potential teachers accept an offer is likely an unambiguously good signal about the quality of a TFA teaching position (Coffman et al., 2014). In contrast, in the present experiment it is not obvious if knowing the number of applicants creates a positive or negative signal. Such information can be a positive cue on the one hand (more applicants may signal a good job) or a negative one on the other hand (more applicants may signal high competition). The reverse should hold true if a scarcity of applicants for a position is revealed. Given the

(2008); Petit (2007); Riach and Rich (2006); Bertrand and Mullainathan (2004); Neumark et al. (1996).

[5]In a related paper Leibbrandt and List (2014) find that women are less likely to negotiate their wage unless explicitly told the wage is negotiable.

[6]See Cialdini et al. (1990); Frey and Meier (2004); Shang and Croson (2006); Martin and Randal (2008); Croson and Shang (2008); Chen et al. (2010); Allcott (2011); Anik et al. (2014); Hallsworth et al. (2014); Mobius and Rosenblat (2014); Smith et al. (2015); Hoxby et al. (2013); Allcott and Rogers (Allcott and Rogers); Chen et al. (2016).

contradictory psychological effects of this particular type of information—which have the potential to cancel each other out—it cannot be clearly predicted whether learning about the number of applicants generally raises, lowers, or has no impact on overall job application rates.

LinkedIn ran this particular experiment as part of their normal business practices. While the experiment wasn't designed to reveal the underlying mechanisms for why more people applied, certain candidate mechanisms, which have heterogeneous treatment effect predictions, can be examined and potentially ruled out. For example, if a herding mechanism is the main driver, then I should observe a larger treatment effect for higher numbers of applicants shown (e.g., a job seeker sees 100 applicants and believes this to be a positive signal of job quality, and is hence more likely to apply).[7] Conversely, if I observe a smaller treatment effect for higher numbers of applicants shown, that would be consistent with a competition aversion mechanism.[8] Since women tend to be more competition averse, finding a more pronounced pattern of a smaller treatment effect for higher numbers for women would be evidence of a competition aversion mechanism.[9] I do not observe heterogeneous treatment effects that are consistent with either a herding or competition aversion mechanism.

There could also be what I will call a "more information" mechanism, whereby simply knowing the number of other applicants reduces information uncertainty and makes job applicants more comfortable with the idea of applying (Gunasti and Ross, 2009). If this mechanism is the main driver, then one would expect experienced job seekers and those viewing job postings from well-known firms to be less affected by the treatment. Additionally, if I do observe a positive treatment effect, this effect may not vary by the number of applicants shown. This mechanism could also be called an ambiguity or risk aversion mechanism.[10] Women are more ambiguity and risk averse, so finding a larger treatment effect for women would be further evidence of a more-information mechanism.[11] I do find some evidence that those viewing less known firms, the less experienced, and female job seekers have larger treatment effects, providing some support for a more-information mechanism.

[7] See Bougheas et al. (2013); Smith and Sørensen (2011); Yechiam et al. (2008); and Anderson and Holt (1997).

[8] It is also possible there is a nonlinear relationship, but I find no evidence of that as described in the Appendix Figure 2. Additionally, it is possible that the two effects are washing out, which I discuss in the Further Analysis section.

[9] See Garratt et al. (2013); Dohmen and Falk (2011); Vandegrift and Yavas (2009); Niederle and Vesterlund (2007); and Gneezy et al. (2003).

[10] 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.

[11] See Garratt et al. (2013); Bertrand (2011); Croson and Gneezy (2009); Eckel and Grossman (2008); Moore and Eckel (2003); Schubert et al. (2000).

In sum, I find that adding information about the number of applicants increases the likelihood that job seekers will apply. This illustrates that companies can employ light-touch and low-cost ways to influence the behavior of job seekers in real-stakes situations.

2 Field Experiment

2.1 Setting

LinkedIn is a large worldwide business networking website with over 350 million members from over 200 regions.[12] LinkedIn has been hosting job postings since 2005, only 2 years after its original launch in 2003.

LinkedIn members are a large and particularly interesting portion of the labor market to study. However, LinkedIn is not representative of the total worldwide labor force. The high-tech and finance industries are heavily represented on this site.[13] These industries have not traditionally had a very diverse workforce.[14] A first step toward a more diverse workforce is a more diverse applicant pool. Because the industries represented on LinkedIn often struggle with diversity, LinkedIn represents an ideal setting for exploring how job seekers decide to apply to job postings.

To use the job postings on LinkedIn, a member can either use the search bar or access the Jobs landing page (see Appendix Figure 4 and Appendix Figure 5), where she can see a number of job postings that are preselected by LinkedIn based on information the member has listed on her profile, such as education, industry, and previous employment. Then the member can click on one of the postings listed. After clicking on a posting, the member sees a full page description of the posting.

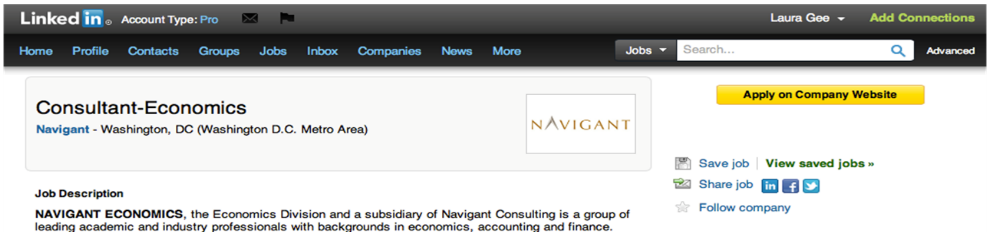
LinkedIn has two types of job postings (see Appendix Figure 6): interior postings, which entail LinkedIn collecting the finished application and forwarding it to the firm, and exterior postings, which link a job seeker to an external website. With interior job postings, I can observe if a user both starts and finishes an application.[15] In the case of exterior postings

[12] 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.

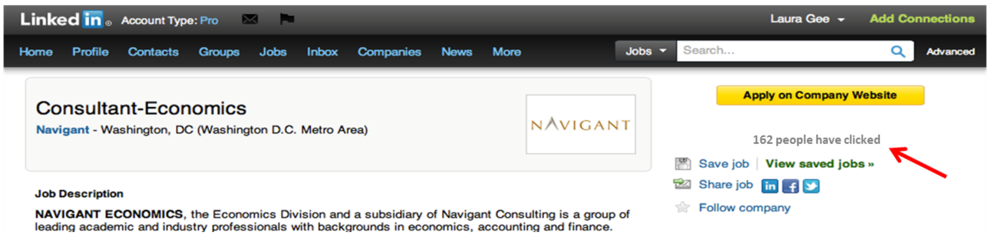
[13] http://www.linkedinppc.com/target-by-industry-company-category/.

[14] For example, only 32.5% of U.S. professionals in STEM-related fields (science, technology, engineering, and mathematics) are female. See http://dpeaflcio.org/programs-publications/issue-fact-sheets/women-in-stem/.

[15] I have the timestamps for when a job seeker clicks "Apply" and for when she submits the 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



(a) Control



(b) Treatment

Figure 1: 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) serves to highlight the treatment for the reader and was not shown to subjects in the experiment. Those in the treatment group 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.

I can observe only if a user starts an application. During the experiment, 61% of the job postings viewed were external.

2.2 Experimental Design

LinkedIn designed and ran the field experiment for 16 consecutive days in March 2012 as part of its regular business practices.[16] LinkedIn members who were actively searching through job postings were randomly assigned to either the treatment or the control condition. For the duration of the experiment, each time a member of the treatment group visited a job posting, she saw the number of current applicants for that job, as pictured in Figure 1.[17] The content of the job postings did not differ between the control and treatment conditions, and in fact 95% of viewed job postings were the same across the two conditions.

LinkedIn chose to randomly assign one-fourth of the active job seekers to the treatment group and the remaining three-fourths to the control group.[18] This is a unique experiment

groups.

[16] To maintain security, LinkedIn has a policy that all analysis is done at LinkedIn using secured computers and networks. This means that to run any new analysis I need to go back to LinkedIn.

[17] For an exterior job posting, the button read "Apply on Company Website." For exterior postings the treatment group was shown the number of started applications. For an interior job posting the button read "Apply Now," and those in the treatment group saw the number of finished applications.

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

because I can observe how two people looking at the exact same posting change their behavior based on whether they know the current number of applicants for that job. 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.

Overall, the sample includes about 2.3 million registered members from 235 countries or areas.[19] There are about 580,000 job seekers in the treatment and 1.7 million job seekers in the control group. During the experiment, those job seekers viewed a total of over 100,000 job postings from 23,000 companies. On average, each job posting was viewed 80 times during the 16 days of the experiment and each firm had about 4.7 jobs posted.[20]

The two main outcome variables 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 somebody spent applying or even if the click on the "Apply" button 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.

2.3 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 (63.5% male). Age is identified for 79% of the sample (mean = 35).[21] The average year when a person became a LinkedIn member is 2009. About 42% of participants are from the U.S., with an average of 315–316 LinkedIn connections as of spring 2013.[22] The subjects are very well educated, with 2% listing an associate's degree, 52% listing a bachelor's degree, and 46% listing a postbachelor's degree as the highest education level

the main experiment.

[19]There are only 193 UN recognized countries, but there are about 245 ISO alpha-2 country codes designating different areas.

[20]The minimum number of views during the 16-day period was one and the maximum was 6,740, with 44 being the median number of views. The minimum number of job postings from a firm was one and the maximum was 2,568, with the median number of postings from a firm being one. Only 78 companies had 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 of both the control and the treatment group had an average of 17–18 current applicants at the beginning of the experiment.

[21]Members do not provide gender, but it is imputed from their country and name by LinkedIn (e.g., Laura in the U.S. is coded female, and Miroslav is coded male in Slovakia). Also, while members do not provide their age it can be imputed based on the year the person graduated from college or high school.

[22]A "link" is a connection between two LinkedIn members that must be approved by both members. For example, a person may ask to be "connected" to a coworker, and then that coworker must approve the connection before it appears on the website. LinkedIn may keep records of an individual's number of connections at the time of viewing, but I did not have access to this information.

attained. Overall, subjects in the control and treatment groups are similar on observable characteristics. There is a statistically significant difference in the proportion of U.S.-based subjects between the two groups, but the magnitude of this difference is extremely small. Beyond country, I do not know more details of the subjects' location.

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	0.635	2,092,347	0.635	1,568,690	0.635	523,657	0	1	0.454
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
U.S.	0.419	2,326,207	0.419	1,743,880	0.418	582,327	0	1	2.233
connections (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	797,023	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.

3 Analysis

This study examines how varying the information that job applicants see impacts their subsequent application choices.

3.1 Main Results

I can observe starting an application for both exterior and interior job postings, but I can observe finishing an application only for interior job postings. For that reason, I will conduct the analysis over two groups: those who saw an exterior posting, and those who saw an interior posting.

It would be interesting to know whether a person takes a job as well as her tenure at the position. However, since less than 3,000 job seekers can be matched to a job at the firm to which they applied, it is impossible to draw any conclusions.

The average number of job postings viewed by both the control and the treatment group was 3.8 (control mean 3.825, treatment mean 3.835, $t = 0.91$) over the 16 days of the experiment. So the treatment does not seem to have a measurable effect on search intensity. This is surprising as one might expect a person in the treatment to search more job postings, because each posting contains more information. Recall randomization is at the member level, and 95% of job postings are seen in the control and treatment. So by design the job postings seen by the control and the treatment group have the same mean number of current applicants (control mean 71.5, treatment mean 71.6, $t = -0.38$).

For the main analysis I restrict the dataset to the first job posting a person views. If I were to look at all the job postings viewed by members in both the control and treatment, one may worry that for those in the treatment group there would be some path dependence. For example, a person who sees job postings with 100, 15, and 10 current applicants may act very differently than a person who sees two, 15, and 10 current applicants. When I restrict the dataset to the first job posting a person views, that leaves a total of 2,326,207 members for analysis.[23] Those are split roughly evenly between first viewing an external job posting (1,134,109) and first viewing an internal job posting (1,192,098).

A simple model might have the left-hand-side variable as $A_{i,j}$, which takes the value 100 if member i starts or finishes an application to job j, and zero if she does not. In this case, the right-hand-side variable would be $T_i = 1$ for treatment-group members who see the number of previously started applications, and $T_i = 0$ for those who do not. By having $A_{i,j}$ take the value 100 when a person applies the coefficient β, the number can be interpreted as the percentage-point difference in likelihood of application from being in the treatment group.

In such a simple model, one may worry that attributes of the job posting might interact with the treatment; however, I do not observe details of the job posting like industry, title, or job description. I can, however, include a job posting fixed effect P_j in the analysis to control for all time-invariant attributes of the job.[24] Since 95% of jobs were seen in both the control and the treatment condition, this does not reduce the sample substantially. I do not know how a member came to view the posting (e.g., through suggestion or via search), but there is no reason to assume that LinkedIn's background algorithm for suggestions and search would differ between the control and the treatment group. I cannot include a member i fixed effect because each member is either always in the control or always in the treatment group.

LinkedIn would not reveal the details of their background search and suggestion algorithms, so I control for variables that are likely used by these algorithms, like the numbers of days posting j has been online during the experiment when viewed by person i ($D_{i,j}$), and the current number of applicants $NumCurrApply_{i,j}$ (even when this is not seen in the

[23] The results using all views by all members are quite similar to those reported in the text. However, a summary of the differences would be quite lengthy; if a reader is interested, these results are available from the author upon request. One may also wonder what was the average total number of applications started for all job seekers. Those in the treatment group start 0.548 applications versus only 0.539 in the control group ($t = 2.29$). See footnote 54 for more details.

[24] I will use this preferred specficiation for the rest of the analysis, but results without a job posting fixed effect are quite similar and are available from the author upon request.

control). $NumCurrApply_{i,j}$ is the true number of current applicants.[25] LinkedIn chose to never display if a job posting had zero applicants, so those views of postings with zero current applicants are omitted from the analysis. The number of current applicants ranges from 1 to $4,125$.[26]

My dependent variables take two values, so a logit model would be appropriate. However, since I am most interested in the average probability of applying, I present the results from a linear probability model in the main text.[27] This leaves me with the following preferred model:

$$A_{i,j} = \beta T_i + P_j + \gamma D_{i,j} + \alpha NumCurrApply_{i,j} + \epsilon_{i,j}. \tag{1}$$

Showing the number of applicants significantly increases the likelihood that a person will start or finish an application as presented in Table 2. This increase holds up to a number of robustness checks.[28]

The absolute magnitude of the observed effect ranges between a 0.089 and a 0.355 percentage-point increase, meaning a proportional increase between 1.964% and 3.707%. This may seem small, but given that during the experimental period an average of 500,000 job postings were viewed each day it could lead to a large increase in applications. A back-of-the-envelope calculation suggests that the treatment would result in an extra 1,500 started and 250 finished applications per day.[29] It could also change the final pool of applicants, which I will explore later.

Although the treatment effect is not very sensitive to the inclusion of the control variables, the coefficients on the control variables are statistically significant. For example,

[25]In a previous version of the paper I chose to divide the number of applicants by 100 because the coefficients on the nonscaled variable are extremely close to zero. Those results are available from the author upon request.

[26]Concentrating on the first posting seen, the mean number of current applicants is 71.5 with standard deviation 181.7. The distribution is 25th percentile, 9; 50th percentile, 26; 75th percentile, 68. The variation in number of current applicants is both across all job postings (standard deviation 181.7) and within a given job posting (standard deviations range from zero to 651.8, with the average standard deviation within a job posting being 4.81).

[27]A logit model yields similar results and is presented in Appendix Table 7.

[28]See Appendix Table 7. This table shows that the treatment is robust to using a conditional logit model (Panel C), clustering standard errors at the job posting level (Panel D), using only jobs seen in both the control and the treatment group (Panel G), using only members who started searching during the experiment (Panel H), and using all the jobs viewed rather than the first job viewed (Panel I). The one robustness check that yields different results entails splitting the sample into U.S. and non-U.S. applicants; here, the coefficients remain positive but lose significance for the U.S. interior job postings (Panel E and F).

[29]First, I assume that those who apply are not substituting this application for another, which seems to be the case given that changes seem to be on the extensive rather than intensive margin, as I will explain later. Second, there are about 275,000 exterior and 280,000 interior postings viewed per day. A 0.349 percentage-point increase in started exterior applications and a 0.208 increase in started interior applications would be a total of about 1,500 started applications. A 0.090 percentage-point increase would be an extra 250 in finished applications.

Table 2: Likelihood of Starting/Finishing an Application

Simple: Without Controls or Fixed Effects			
	1	**2**	**3**
	Start Ext	**Start Int**	**Finish Int**
Treatment	0.355***	0.225***	0.094**
	(0.065)	(0.065)	(0.034)
Adj R2	0.000	0.000	0.000
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	3.689%	2.125%	3.707%
Preferred: With Controls and Job Fixed Effects			
	1	**2**	**3**
	Start Ext	**Start Int**	**Finish Int**
Treatment β	0.349***	0.208**	0.089**
	(0.065)	(0.065)	(0.034)
Days Posted	-0.064***	-0.064***	-0.064***
	(0.007)	(0.008)	(0.004)
NumCurrApply	-0.007***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.000)
Adj R2	0.049	0.052	0.013
Pct Increase $\frac{\beta}{\overline{A}_{T=0}}$	3.626%	1.964%	3.508%
N	1,134,109	1,192,098	1,192,098
Control Mean $\overline{A}_{T=0}$	9.623	10.589	2.536

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2), and zero otherwise. In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting), and zero otherwise. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

increasing the number of applicants by one decreases the likelihood of application by 0.007–0.010 percentage points. This is a relatively small decrease given that the median number of applicants is 21, and the 90th percentile is 133.

3.2 Candidate Mechanisms

Understanding the mechanisms behind the increased application rate could allow firms to target those from whom they want additional applications. Unfortunately, the experiment was not designed to trace out the mechanism for why a person is more likely to apply, but some candidate mechanisms have heterogeneous-treatment-effects predictions that I will explore in this section.

3.2.1 Competition-Aversion Mechanism

Seeing many applicants could signal that a job is highly competitive and may deter a competition-averse person from applying.[30] In this case, the treatment effect should decrease as the number shown rises. Conversely, if a herding mechanism is the driver, then the treatment effect should be positive for larger versus smaller numbers of applicants shown. While both can conceivably take place, from a policy perspective the overall effect is most important. In the Further Analysis section I will show that there are indeed some people who seem competition averse and some that are herding. In this section I will show that under a number of specifications there is no consistent pattern of either competition aversion or herding in the data.

The exact number of current applicants shown on the posting can be thought of as pseudorandom because it is largely determined by when a person is searching on LinkedIn (Smith et al., 2015). To avoid issues of the order of viewing postings affecting the treatment effect, I begin by using only the first posting seen.

I begin by using a nonlinear model to plot the treatment effect by the number shown in Figure 2.[31] On the vertical axis of Figure 2 is the percentage-point difference in the

[30]Here I use the term *competition averse* to mean someone who, with everything else being equal, is less likely to apply to a job posting with more applicants. Someone would be more competition averse the more they decreased their likelihood of application in response to a single extra applicant.

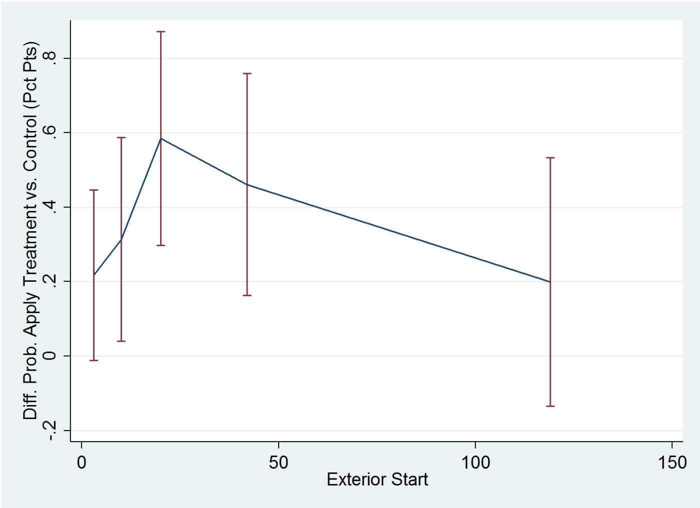
[31]I created a model with quantile bins for the number of current applicants. The number of applicants was broken into five equal-sized quantiles $QNumCurrApply_{i,d,j}$ and then interacted with the treatment as in the equation below:

$$A_{i,d,j} = \beta T_i + \lambda T_i * QNumCurrApply_{i,d,j} + \alpha QNumCurrApply_{i,d,j} + P_j + D_d + \epsilon_{i,d,j}.$$

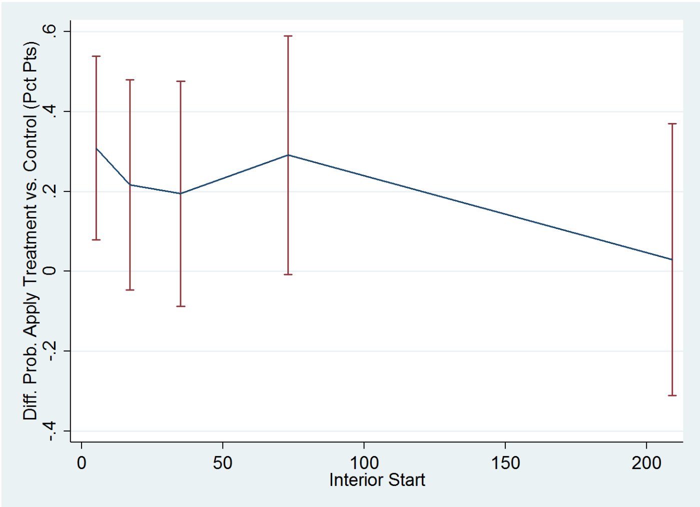
I have also used bins of the numbers 0–25, 26–49, ... 200+, or bins of numbers 0–49, 50–99, ... 200+. The graphs show a similar lack of pattern. Figure 2 graphically represents the results from this model.

likelihood of applying between the treatment and the control groups. On the horizontal axis is the number of applicants shown in the treatment group. The error bars show the 95% confidence interval around each predicted difference. If competition avoidance is the dominant effect, one would expect a downward sloping trend in the panels of Figure 2. On the other hand, if herding is the dominant effect, one would expect to see an upward-sloping trend.[32] However, there is no clear or consistent pattern of either competition aversion or herding, especially when one takes into account the wide error bars.

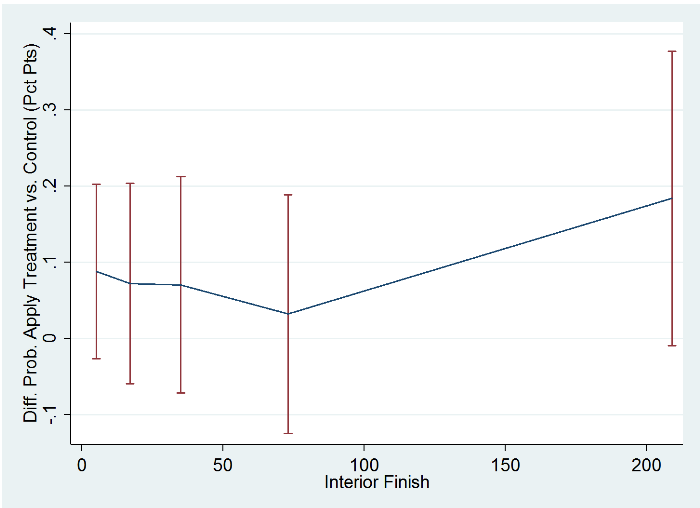
[32]If one uses all the views, the graphs show a similar lack of a pattern. Additionally, if one uses the difference between the number of applicants seen on a current job posting and the number seen on a previously viewed posting, the graphs show a similar lack of a pattern. These graphs and underlying regressions are available from the author upon request.



(a) Exterior: Starting Application



(b) Interior: Starting Application



(c) Interior: Finishing Application

Figure 2: Plots of Coefficients on Treatment Dummy Variable by Number of Applicants Shown

Notes: The coefficients are plotted at the median of each quantile.

Next, I interact the treatment with the number of applicants ($Treatment{*}NumCurrApply$), but the coefficient on this interaction is not consistent in sign and is statistically insignificant (Table 3, Panel A).[33]

Table 3: Heterogeneous Treatment Effects by Number Shown

	1	2	3
	Start Ext	**Start Int**	**Finish Int**
	A. First View Only		
Treatment	0.366***	0.211**	0.072+
	(0.067)	(0.073)	(0.039)
Treatment*NumCurrApply	-0.000	-0.000	0.000
	(0.000)	(0.001)	(0.000)
NumCurrApply	-0.007***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)
Adj R2	0.049	0.052	0.013
N (members)	1,134,109	1,192,098	1,192,098
	B. All Views		
Treatment	0.355***	0.205***	0.050+
	(0.049)	(0.051)	(0.026)
Treatment*NumCurrApply	-0.001+	-0.000	0.000
	(0.000)	(0.000)	(0.000)
NumCurrApply	-0.005***	-0.007***	-0.009***
	(0.001)	(0.001)	(0.000)
Adj R2	0.056	0.053	0.019
N (members)	1,134,109	1,192,098	1,192,098
Member-view observations	4,499,007	4,405,032	4,405,032
	C. Current Num - Member Specific Avg Num Apply		
Treatment	0.317***	0.192***	0.066**
	(0.047)	(0.047)	(0.024)
Treatment*(NumCurrApply-MemAvgNumApply)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
(NumCurrApply-MemAvgNumApply)	-0.003***	-0.006***	-0.001***
	(0.000)	(0.000)	(0.000)
Adj R2	0.056	0.053	0.018
N (members)	1,134,109	1,192,098	1,192,098
Member-view observations	4,499,007	4,405,032	4,405,032
	D. Current Num - Prev Num		
Treatment	0.281***	0.142*	0.027
	(0.062)	(0.063)	(0.034)
Treatment*(NumCurrApply$_t$-NumCurrApply$_{t-1}$)	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
(NumCurrApply$_t$-NumCurrApply$_{t-1}$)	-0.002***	-0.003***	-0.001***
	(0.000)	(0.000)	(0.000)
Adj R2	0.060	0.055	0.022
N (members)	940,289	932,591	932,591
Member-view observations	3,364,898	3,212,934	3,212,934

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2). In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting). Includes job posting fixed effects and days posted. Panel B and C include data for every job posting viewed by the 2.3 million members; observations are weighted so that each member's weights sum to 1, and standard errors are clustered at the member level. Panel D includes data for all but the first job posting viewed by the 1,248,289 members with 2+ views, observations are weighted so that each member's weights sum to 1, and standard errors are clustered at the member level. Legend: + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

So far I have concentrated on the first job viewed so now I expand the dataset, so that it includes the same 2.3 million members but now uses all their views of over 8 million job

[33] The coefficients on $Treatment * NumCurrApply$ are 0.028 to 0.019. Even if these point estimates were more exact, they imply a weak relationship because 100-applicant increases are uncommon ($NumCurrApply$ median = 26, mean= 71). Also, a quadratic model yields noisy estimates. Results available from author upon request.

postings. I find that the coefficients on $Treatment * NumCurrApply$ are still neither consistent in sign nor statistically significant for starting or finishing an interior job application. Yet for those viewing an exterior job posting, the treatment effect decreases by 0.001 percentage points for every extra applicant increase—a result statistically significant at the 10% level. This provides preliminary evidence in favor of a weak competition-aversion mechanism (Table 3, Panel B).

The noise seen in the data could result from job seekers' inability to interpret the absolute number seen.[34] For example, Eleanor might think that 25 applicants is a high number, while Dan may perceive the same number to be low. I compute the average number of current applicants for all postings viewed by a member ($MemAvgNumApply$).[35] I then use the difference between the number of applicants for the currently viewed posting and the average. The coefficients for the interaction $Treatment * (NumCurrApply - MemAvgNumApply)$ are zero and not statistically significant (Table 3, Panel C).

Last, an alternative way to benchmark a number as low or high is to use the difference in the number of applicants between the currently and the previously viewed posting ($DiffNumCurrApply = NumCurrApply_t - NumCurrApply_{t-1}$). This requires restricting the data to the 1.2 million members who view at least two job postings.[36] The coefficients for the interaction between $DiffNumCurrApply$ and the treatment are neither consistent in sign nor statistically significant (Table 3, Panel D).

Since previous work finds that women are more competition averse, one might expect competition aversion to be greater for women than men.[37] The coefficient for the interaction between $Treatment$ and $NumCurrApply$ is neither consistently negative nor statistically significant for female job seekers (See Table 4).

The original experiment was not designed to test for competition aversion, though there are some heterogeneous-treatment-effects predictions that would be consistent with competition aversion. However, there is no consistent pattern of a decline in the treatment effect for

[34] To gain further insight into the findings, in June 2014 I administered an online survey meant to uncover how job seekers interpret the number of applicants. This survey presented respondents with a hypothetical job-posting scenario that included the number of applicants. The results show that 50% of respondents use this information to avoid competition, 22% to herd toward more popular jobs, and 27% to avoid ambiguity. While the majority of respondents indicate being competition averse, they differ in what number constitutes high competition. See Appendix Section 6.2 for details.

[35] A single average is computed for each person over all postings viewed (pooling exterior and interior) because it seems likely members would not keep a separate average in their head for internal and external postings.

[36] This results in losing about half the sample. This subsample is balanced on observables across the control and treatment. The subsample is similar to the full sample with the exception of having 20 more LinkedIn connections.

[37] See Garratt et al. (2013); Dohmen and Falk (2011); Vandegrift and Yavas (2009); Niederle and Vesterlund (2007); and Gneezy et al. (2003). Note that 94% of jobs are seen by both male and female job seekers.

more applicants shown. Another candidate mechanism is a more-information mechanism, which I explore in the next section.

3.2.2 More-Information Mechanism

I will use the term "more information" to refer to a mechanism by which simply providing additional information about the job posting increases one's likelihood of applying. This could be because it is difficult to determine that a posting is legitimate, so seeing the number of current applicants legitimizes the posting. If more information is the main driver, then the treatment effect should be more pronounced for the risk/ambiguity averse (e.g., women), for inexperienced job seekers, and for those viewing postings from lesser known firms. Additionally, unlike the predictions described in the previous section, the specific number of applicants may not moderate the magnitude of the treatment effect.[38]

Job seekers who are ambiguity averse may experience stronger benefits from more information (Ellsberg, 1961). Ambiguity aversion can be modeled as a specific form of risk aversion (Halevy and Feltkamp, 2005). Since women are generally more ambiguity or risk averse, finding a larger treatment effect in this subpopulation would be evidence of a more-information mechanism.[39] The treatment effect is directionally larger for women than men; however, the difference is only statistically significant for finishing an interior application (see Table 4).[40] Also, it is important to note that the treatment effect for men is only statistically greater than zero for one of the three outcome variables.[41] Last, the treatment effect does not vary by the number shown as evidenced by the insignificant coefficients on $Treatment*NumCurrApply$ and $Treatment*Male*NumCurrApply$ in Panel B of Table 4. This provides some evidence in support of a more-information mechanism.

In addition to being supportive of a more-information mechanism, the finding that women are more affected than men could be used to increase the number of female applicants. Indeed, large employers of highly skilled workers in the U.S. have recently explicitly stated they would like to close the gender gap in their firms.[42] Also, previous research finds that

[38] For example, think of a badge that states "someone has applied" rather than "X people have applied." Knowing that someone applied still increases the level of information and doesn't require knowing the specific number of applicants.

[39] See Garratt et al. (2013); Bertrand (2011); Croson and Gneezy (2009); Eckel and Grossman (2008); Moore and Eckel (2003); Schubert et al. (2000).

[40] The coefficients for women are statistically larger if I use all 8 million views and do not cluster standard errors at the member level (results available from author by request and reported in a previous draft of this paper).

[41] In Panel A of Table 4 the linear combination of $Treatment$ and $Treatment * Male$ is 0.127 $t = 1.48$ for starting and 0.041 $t = 0.91$ for finishing an interior application. In Panel B of Table 4 the linear combination of $Treatment$ and $Treatment * Male$ is 0.120 $t = 1.26$ for starting and 0.023 $t = 0.45$ for finishing an interior application.

[42] For example, in May 2014 Google announced that only 30% of its workforce is female, and

increased gender diversity in the workforce has positive results for the firm (Weber and Zulehner, 2014, 2010; Hellerstein et al., 2002). So this may be a light-touch low-cost intervention to increase the number of female applicants, and perhaps eventually the gender balance in some firms. I will speak more about this in the Further Analysis section below.

Table 4: Heterogeneous Treatment Effects by Gender

	1	**2**	**3**
	Start Ext	**Start Int**	**Finish Int**
A. Gender			
Treatment	0.383***	0.302**	0.212***
	(0.111)	(0.112)	(0.058)
Treatment*Male	-0.033	-0.174	-0.170*
	(0.141)	(0.141)	(0.074)
Male	1.102***	1.426***	0.498***
	(0.073)	(0.074)	(0.038)
NumCurrApply	-0.007***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)
Adj R2	0.049	0.052	0.013
N	1,020,017	1,072,330	1,072,330
B. Gender + Number Seen			
Treatment	0.421***	0.242+	0.162*
	(0.114)	(0.125)	(0.066)
Treatment*NumCurrApply	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Treatment*Male	-0.068	-0.122	-0.138+
	(0.144)	(0.155)	(0.083)
Treatment*Male*NumCurrApply	0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Male	1.102***	1.425***	0.498***
	(0.073)	(0.074)	(0.038)
NumCurrApply	-0.007***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)
Adj R2	0.049	0.052	0.013
N	1,020,017	1,072,330	1,072,330

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2), zero otherwise. In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting), zero otherwise. Includes job posting fixed effects and days posted. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Intuitively, novices need more information than experienced job seekers, so the treatment effect should be larger for novices. I use the number of years a person has been a LinkedIn member as a proxy for job-search experience (mean: 3.047, standard deviation: 2.108, min: 0, max: 9).[43] The treatment effect is larger for inexperienced job seekers for two of the three

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/.

[43] Age and membership years have a correlation coefficient of 0.31. Including age in the models in Table 5

outcomes.[44] Last, the treatment effect does not vary by the number shown as evidenced by the insignificant coefficients on $Treatment * NumCurrApply$ and $Treatment * YearsMem * NumCurrApply$ for two of the three outcome variables and the significant coefficients are quite close to zero in Panel B of Table 5. These results are supportive of a more-information mechanism.

Table 5: Heterogeneous Treatment Effects by Experience

	1	2	3
	Start Ext	**Start Int**	**Finish Int**
A. Experience (Years LinkedIn Member)			
Treatment	0.508***	0.313**	0.216***
	(0.121)	(0.117)	(0.058)
Treatment*YearsMem	-0.051+	-0.036	-0.043**
	(0.030)	(0.030)	(0.015)
YearsMem	-0.255***	-0.378***	0.130***
	(0.016)	(0.016)	(0.008)
NumCurrApply	-0.007***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)
Adj R2	0.049	0.053	0.013
N	1,134,109	1,192,098	1,192,098
B. Experience (Years LinkedIn Member)+Number Seen			
Treatment	0.546***	0.284*	0.283***
	(0.125)	(0.130)	(0.064)
Treatment*YearsMem	-0.057+	-0.024	-0.070***
	(0.031)	(0.033)	(0.017)
Treatment*NumCurrApply	-0.001	0.000	-0.001+
	(0.001)	(0.001)	(0.000)
Treatment*YearsMem*NumCurrApply	0.000	-0.000	0.000*
	(0.000)	(0.000)	(0.000)
NumCurrApply	-0.007***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)
YearsMem	-0.255***	-0.378***	0.130***
	(0.016)	(0.016)	(0.008)
Adj R2	0.049	0.053	0.013
N	1,134,109	1,192,098	1,192,098

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2). In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting). Includes job posting fixed effects and days posted. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Just as inexperienced job seekers need more information than experienced, a person viewing a listing from an unknown firm will need more information than a person viewing a listing from a well-known firm, so the treatment effect should be smaller for well-known firms.

does not change the sign or significance of the coefficients on $Treatment * YearsMem$, but does reduce the sample size (results available from author upon request).

[44] A back-of-envelope calculation finds the treatment to be half as effective after 2.5 more years of LinkedIn membership (see column 3 of Table 5 Panel A). For a person who joined during the present year, the treatment increases the likelihood of finishing an application by 0.216. Since half that effect would be 0.108, each year of membership decreases the treatment effect by 0.043. That implies that after 2.5 years the treatment is half as effective, $0.108/0.043 = 2.5$.

I identify well-known firms by matching firm name to the 2,000 biggest public firms from Forbes.[45] Because only 13% of well-known-firm job postings are interior, I will concentrate on the results for exterior postings.[46] For exterior job postings the treatment effect is smaller for well-known firms as shown in column 1 of Panel A of Table 6. Interestingly, for well-known firms the treatment effect increases as the current number of applicants shown increases, yet for less known firms the treatment effect decreases as the current number of applicants shown increases, as shown in column 1 of Panel B of Table 6. This might be because when one sees a high number of applicants at a firm like Google that signals a higher quality position, but because of Google's size one believes they will simply hire more workers if they interview more qualified candidates.[47] Whereas for a less known and possibly smaller firm there is more likely to be only a single vacancy, so one views higher number of applicants as a clearer signal of competition.

This experiment was not designed to test for underlying mechanisms, but evidence of higher treatment effects for women, inexperienced job seekers, and less known firms are consistent with a more-information mechanism.

[45]The Forbes 2000 is a list of the 2,000 biggest public companies (http://www.forbes.com/global2000/list/). Research assistants were able to match 1.702% of the firms in our main analysis to a firm listed on the Forbes 2000 list. Research assistants also attempted to match firm names to those in the Reference USA database, but the match rate was two-thirds as large at 1.095%.

[46]In contrast, 51% of less known firm job postings are exterior and 49% are interior.

[47]LinkedIn clearly states that each posting is meant to be for a single vacancy, but this policy is likely unknown to job seekers.

Table 6: Heterogeneous Treatment Effects by Firm Type

	1 Start Ext	2 Start Int	3 Finish Int
A. Known Firm			
Treatment	0.431***	0.253***	0.093**
	(0.077)	(0.069)	(0.035)
Treatment*KnownFirm	-0.262+	-0.304	0.003
	(0.139)	(0.222)	(0.114)
KnownFirm	2.234***	1.336***	0.404***
	(0.070)	(0.111)	(0.057)
Adj R2	0.001	0.000	0.001
N	1,134,109	1,192,098	1,192,098
Postings from KnownFirm	347,918	113,487	113,487
B. Known Firm + Number Seen			
Treatment	0.536***	0.253**	0.075+
	(0.078)	(0.078)	(0.040)
Treatment*KnownFirm	-0.817***	-0.172	0.030
	(0.152)	(0.254)	(0.133)
Treatment*KnownFirm*NumCurrApply	0.009***	-0.002	-0.000
	(0.001)	(0.001)	(0.001)
Treatment*NumCurrApply	-0.002***	-0.000	0.000
	(0.000)	(0.001)	(0.000)
NumCurrApply	0.007***	0.017***	0.006***
	(0.000)	(0.000)	(0.000)
KnownFirm	2.198***	1.165***	0.348***
	(0.072)	(0.115)	(0.060)
Adj R2	0.004	0.009	0.004
N	1,134,109	1,192,098	1,192,098
Postings from KnownFirm	347,918	113,487	113,487

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2), zero otherwise. In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting), zero otherwise. Includes days posted as a control variable. These models do not include a job posting fixed effect. Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

4 Further Analysis

Showing the number of applicants increases the likelihood of application and might be used to increase applications from women, the less experienced, and to less known firms. As aforementioned many large firms have publicly announced that they would like to increase gender balance in their hiring. There has been less media coverage of initiatives to hire inexperienced workers or to drive applicants to less known firms. However, before I can recommend the intervention of showing the number of current applicants to increase applications overall or from any subgroup, there are some further analyses that I need to address in this section.

4.1 Are women more likely to apply to masculine jobs?

On LinkedIn men are more likely to start an application than women.[48] About 10% of the job postings have only women applying in the control condition, so increasing the number of female applicants for these jobs does nothing to increase female applications to male-dominated positions. I do not have access to the actual job-posting description, so I cannot use job attributes to categorize jobs as masculine. Instead I define a job as "masculine" if over 80% of those who started or finished an application in the control group were men.[49] Note that although behavior by those in the control group defines a job as "masculine," individuals in both the control and treatment group view these job postings. I can only determine the proportion of male applicants for jobs that have at least one applicant with gender known in the control. To be consistent I restrict the data to those viewing a job that has at least one applicant of known gender in both the control and the treatment.[50] Using a model without job-fixed effects, I interact the $MasculineJob$ variable with the treatment for men and women. I find that showing the number of applicants increases the likelihood

[48] If I control for the type of job posting with a job-fixed effect, I find that the likelihood of starting an exterior application is 9.775% for men, but only 8.687% for women. Similarly, the likelihood of starting an interior application is 10.599% for men, but only 9.931% for women. Last, the likelihood of finishing an interior application is 2.674% for men, but only 2.179% for women.

[49] To be consistent with the main analysis I use only the first job viewed by those in the control group. About 40% of the jobs are "masculine" if the 80% cutoff is used. The results are similar using other thresholds (results available from author upon request).

[50] Restricting the sample to only those who viewed an application with at least one person of known gender who started an application in the control and treatment results in losing 49% to 58% of the sample. Restricting to only those who viewed an application with at least one person of known gender who finished an application in the control and treatment results in losing 76% of the sample for finishing an interior application. So these are highly selected subsamples. The subsamples are balanced on the observable characteristics across the control and the treatment, so these results should be internally valid. The members in these subsamples look similar to the whole sample, except for the proportion of U.S. members dropping by 15–28 percentage points, and the number of LinkedIn connections being higher by 30–50 (since the rate of starting/finishing an application is higher outside the U.S. and for those with more connections). Therefore these results are less externally valid.

of a female job seeker starting or finishing a masculine job application.[51] So this light-touch intervention has the desirable effect of increasing the likelihood of a woman applying for a masculine job, which could help ameliorate the gender occupation gap.

4.2 Is there too much congestion from the increased application rate?

Even if more women apply for masculine jobs, diversity could still be hindered if hiring managers are being overloaded with too many applicants. If the treatment causes people to apply for jobs that ultimately end up with a large number of applicants, that could actually harm an applicant's chances of receiving an offer. While the data do not record job offers, I do have data on the final number of applications started or finished for each job by the end of the experimental period.[52] I scale this by the number of days the job posting was online during the experiment to get a measure of job congestion, and create a *Congested* variable that takes the value 1 if a job has an above-average number of final applications per day.[53] I find that the interaction of the treatment with *Congested* is never statistically significant (results available from the author upon request) for either gender. This result means that showing the number of applicants does not cause people to apply for more congested jobs.

4.3 Is this encouraging new applicants?

Since each woman can ultimately take one only job, increasing the number of jobs she applies to may not actually increase workforce diversity. I therefore explore whether the observed increase reflects new applicants (extensive margin) rather than an increase in applications from current applicants (intensive margin) during the 16 days of the experiment. Across both genders, as well as for female job seekers alone, the treatment group starts more applications than does the control. However, when looking only at those with at least one application, that

[51]See Appendix Table 8. Note the coefficient on "MasculineJob" is mechanically negative in this model because it represents the liklihood a female job seeker will apply to a "MasculineJob" in the control group, which by definition is lower than the likelihood of a male job seeker. However, in this model the effect of the treatment on female job seekers viewing a masculine job is the sum of the coefficients on "Treatment"and "Treatment*StartMasculine". So the mechanically negative coefficient on "MasculineJob" does not interfere with our interpretation. One could obtain the same results by running the model on only women viewing a so-called "MasculineJob." Female job seekers in the treatment (versus the control) are 11.696 percentage points more likely to start an application for an exterior "masculine" job, 8.792 percentage points more likely to start an interior "masculine" job application, and 4.719 percentage points more likely to finish the interior application. All effects are statistically significant at the 1% level. Part of the reason why the coefficients are so large is that the starting/finishing rate is about 40% larger for this subsample.

[52]This is different from the number shown, since that is a running tally of applicants.

[53]Recall that over 90% of jobs are seen in both the control and treatment, hence I cannot use the number of applications started/finished in the control.

difference goes away. This means that the treatment increases the number of applications on the extensive margin.[54] Since many job searches last longer than 16 days, this is suggestive but not conclusive evidence that the treatment is adding to the thickness of the applicant pool by encouraging those who otherwise would not have started an application to apply.

4.4 Are competition aversion and herding both taking place?

Earlier I showed that there is no consistent pattern of competition aversion overall. However, if both competition aversion and herding are taking place simultaneously this could explain the lack of an overall pattern. From a policy perspective, the overall pattern matters, but one may also wonder if there are herding types and competition-averse types. The treatment was assigned at the individual member level, so a member sees the number of applicants either always or never. I restrict the data to those in the treatment group who have some variation in starting an application (98,070 members), because it is not possible to observe herding or competition aversion if someone never applies or always applies. I then compute the correlation between starting an application and the number shown.[55] I find that the mean correlation is 0.043, quite close to zero. However, as shown in Figure 3, almost half of the members have a positive correlation (e.g., herding) and the other half a negative correlation (e.g., competition aversion).[56] This is consistent with herding and competition aversion both occurring simultaneously, which would explain why there is no overall pattern by number seen. Being a herding or competition-averse type can only be determined for those in the treatment group, so I cannot make statements about differential treatment effects across these types.[57]

[54] For all job seekers, those in the treatment group start 0.548 applications versus only 0.539 in the control group ($t = 2.29$). Yet looking only at those who apply to at least one job, those in the treatment start 2.532 applications, while those in the control start 2.549—a statistically insignificant difference ($t = 0.987$). The same pattern holds for finishing applications, though the differences are never statistically significant. For female job seekers, those in the treatment group start 0.493 applications versus only 0.481 for this in the control group ($t = 2.1$). Yet for those who apply to at least one job, the difference is not statistically significant ($t = 0.810$).

[55] I use views of both external and internal job postings because if I restrict to certain types of postings I lose even more of the sample.

[56] The distribution of correlations is quite similar across genders (Appendix Figure 11). One might also wonder if those who saw higher numbers also tended to have more negative correlations. Appendix Figure 12 plots the average correlation by number seen in the treatment. There is no concentration of negative correlations for higher numbers shown.

[57] Note this same pattern of half herding, half competition aversion could also be explained by randomly generated data. But the distributions of types have peaks at -1 (a person who didn't apply when they saw a higher number) and 1 (a person who only applied when they saw a higher number), and are centered around 0 with a smooth tail moving toward either extreme. One might expect purely random data to have a more uniform distribution.

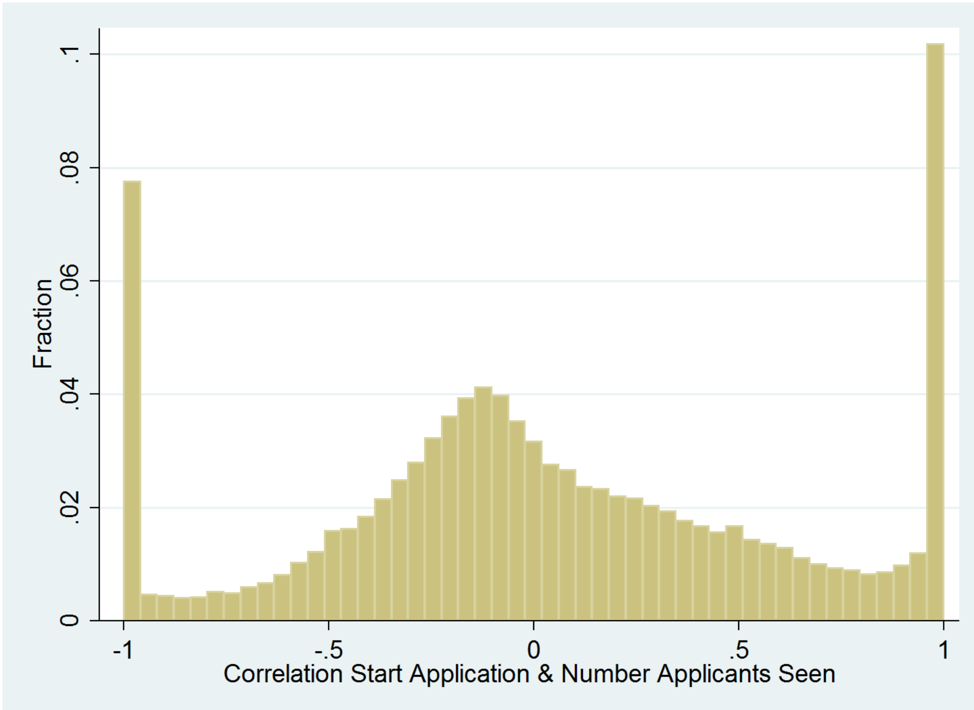


Figure 3: Distribution of Correlation Between Number Seen and Starting Application

Note: This figure shows the distribution of the correlation between number seen and starting an application for those in the treatment who have some variation in whether they apply (98,070). A correlation closer to -1 is evidence of competition aversion. A correlation of 1 is evidence of herding.

5 Conclusion

Previous labor market field experiments have concentrated on fictitious job seekers, or applicants to specific types of positions (administrative or teaching). This study is able to observe 2.3 million real job seekers on LinkedIn who look at over 100,000 real job postings. I find that showing the number of current applicants on the corresponding job posting increases a job seeker's likelihood of applying by 1.9%–3.6%. Interestingly, job seekers in both the control and treatment group view about 3.8 job postings, so search intensity is not affected by the treatment.

Understanding the mechanism for increased applications could increase welfare through a better functioning labor market. If a more-information mechanism dominates, then this may enhance welfare by increasing the thickness of the market and could be used as a strategic tool for targeting minorities. By contrast, if a competition-aversion mechanism dominates, there may be a welfare gain from decreased congestion, but also a decrease in the number of minority applicants. I find that women (especially those who apply for male-dominated jobs), inexperienced job seekers, and those looking at less known firms are more affected by the treatment. This implies that a more-information mechanism may be at play.

Importantly, showing the information does not simply push female applicants toward already female-dominated jobs, and it does not overly increase congestion, so that hiring managers would be overloaded. Instead, it brings new job seekers into the applicant pool.

Previous labor market field studies have shown that changing the pay structure can result in a large increase in minority applications (e.g., Flory et al. (2015) find that removing competitive pay halves the application gender gap). However, changing the pay structure is a relatively large change to the firm's business practices. This study finds that simply showing the number of applicants increases the likelihood that a woman will finish an application by 0.162 percentage points, versus a zero effect for men. Although this increase is smaller than one that could be obtained from changing the pay structure, showing the number of applicants is likely a more easily implementable change. Because this change is quite simple at the time of writing, LinkedIn allowed firms to choose whether they would like to show this information on their job postings.

A shortcoming of the current study is that it may not generalize to nonprofessional labor markets. LinkedIn is primarily used by those holding a bachelor's degree or higher, so it is not clear that showing the number of current applicants would have the same effect in a labor market for less educated workers.

Additionally, LinkedIn did not design this study with the hopes of isolating the mechanism for why showing the number of current applicants might change behavior. Partnering earlier in the research process with large firms during field experiments could be beneficial to both furthering our knowledge and the firm's bottom line. However, using "found" experiments like this one is a first step toward showing firms the value that academics can bring to their business practices. Behavioral "nudges" have become popular tools for policy makers and firms to influence short-term behavior. Recently, Coffman et al. (2014) have shown that an information nudge has large long-term effects on job applicants accepting and staying at a teaching job. Understanding how light-touch nudges can be used to affect both long-term and short-term behavior in the job market is an important area for continued research.

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6 Appendix (For Online Publication)

6.1 Setting

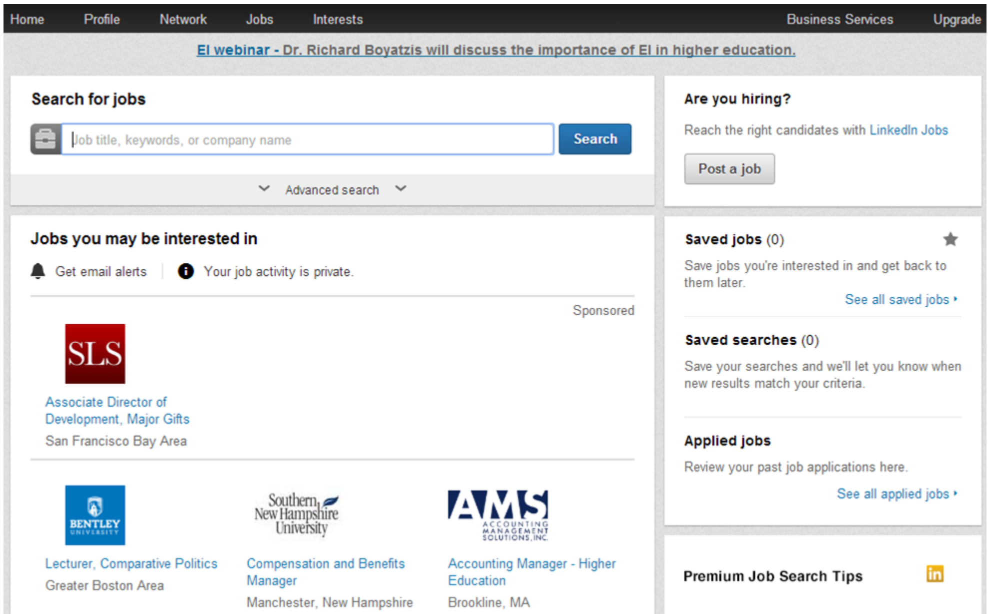


Figure 4: Jobs Landing Page

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

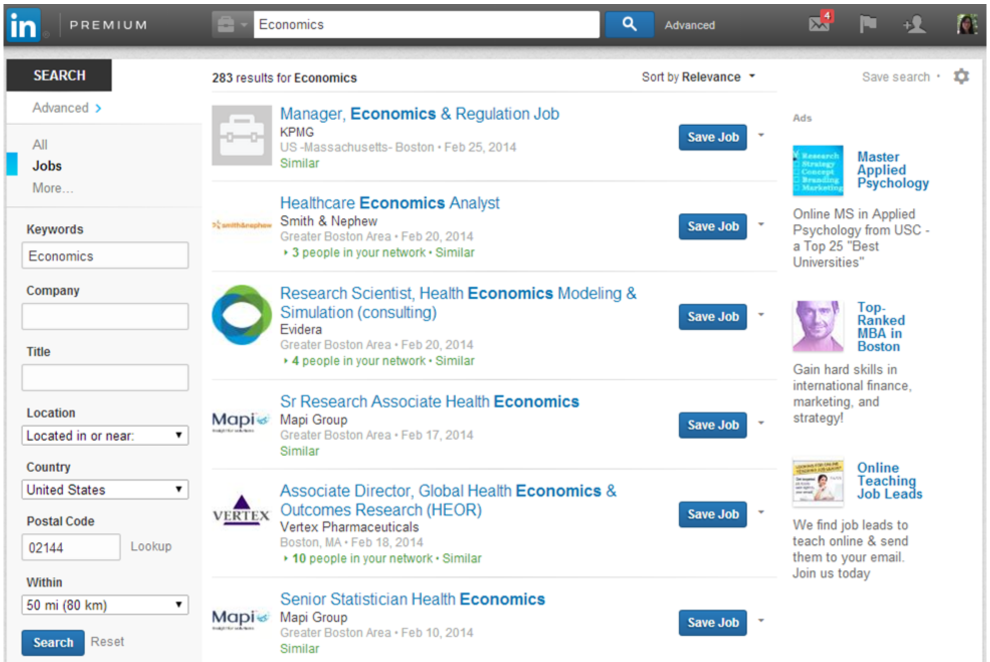
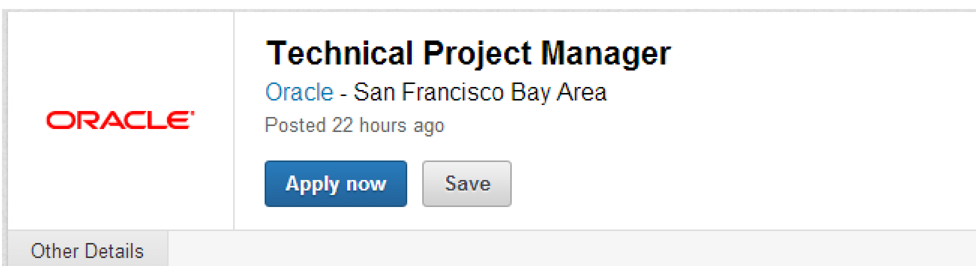
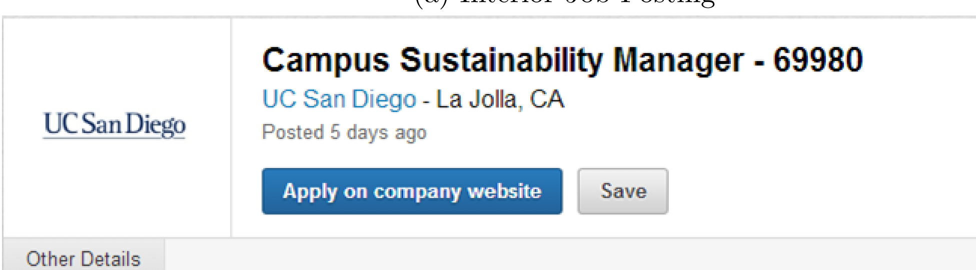


Figure 5: Job Search Landing Page

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



(a) Interior Job Posting



(b) Exterior Job Posting

Figure 6: 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 versus control screenshots in Figure 1.

Table 7: Main Results Robustness Checks

	1	2	3
	Start Ext	**Start Int**	**Finish Int**
A. Without Controls or Fixed Effects			
Treatment	0.355***	0.225***	0.094**
	(0.065)	(0.065)	(0.034)
Adj R2	0.000	0.000	0.000
N	1,134,109	1,192,098	1,192,098
B. Preferred Main Results			
Treatment	0.349***	0.208**	0.089**
	(0.065)	(0.065)	(0.034)
Adj R2	0.049	0.052	0.013
N	1,134,109	1,192,098	1,192,098
C. Logit with Fixed Effects			
Treatment	0.041***	0.023**	0.035**
	(0.008)	(0.007)	(0.014)
Adj R2			
N	944,489	1,049,361	717,813
D. Clustered Errors at Job Level			
Treatment	0.355***	0.225***	0.094**
	(0.064)	(0.065)	(0.033)
Adj R2	0.000	0.000	0.000
N	1,134,109	1,192,098	1,192,098
E. U.S. Only			
Treatment	0.325***	0.143	0.078
	(0.096)	(0.106)	(0.049)
Adj R2	0.039	0.030	-0.003
N	527,193	446,921	446,921
F. Non-U.S. Only			
Treatment	0.415***	0.231**	0.097*
	(0.091)	(0.084)	(0.047)
Adj R2	0.061	0.064	0.017
N	606,916	745,177	745,177
G. Jobs in Control and Treatment			
Treatment	0.349***	0.208**	0.089**
	(0.065)	(0.065)	(0.034)
Adj R2	0.047	0.052	0.013
N	1,130,546	1,190,953	1,190,953
H. Start Search During Experiment			
Treatment	0.365***	0.227**	0.086*
	(0.069)	(0.069)	(0.036)
Adj R2	0.049	0.053	0.012
N	1,007,804	1,056,338	1,056,338
I. All Observations (not just first view)			
Treatment	0.242***	0.169***	0.048*
	(0.035)	(0.039)	(0.023)
Adj R2	0.039	0.049	0.019
N	4,499,007	4,405,032	4,405,032

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2), zero otherwise. In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting), zero otherwise. In Panel C I had to omit one of the job postings because the results would not converge while it was included. Legend: + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 8: Likelihood Apply to Masculine Job

	1 **Start Ext**	2 **Start Int**	3 **Finish Int**
Treatment	0.938***	0.381*	0.486*
	(0.210)	(0.193)	(0.197)
Treatment*MasculineJob$_S$	10.759***	8.412***	
	(0.402)	(0.377)	
Treatment*Male*MasculineJob$_S$	-12.375***	-9.587***	
	(0.490)	(0.454)	
Male*MasculineJob$_S$	14.182***	12.385***	
	(0.253)	(0.233)	
Treatment*Male	3.841***	2.814***	1.584***
	(0.289)	(0.263)	(0.269)
MasculineJob$_S$	-11.357***	-10.844***	
	(0.209)	(0.194)	
Male	-3.425***	-2.440***	-1.248***
	(0.146)	(0.133)	(0.136)
Treatment*MasculineJob$_F$			4.234***
			(0.346)
Treatment*Male*MasculineJob$_F$			-4.778***
			(0.425)
Male*MasculineJob$_F$			5.784***
			(0.216)
MasculineJob$_F$			-4.781***
			(0.176)
N	481,648	614,674	282,986

Notes: The dependent variable takes the value 100 if a job seeker starts an exterior application (column 1) or interior application (column 2), zero otherwise. In column 3 the dependent variable takes the value 100 if a job seeker finishes an interior application (not conditional on starting), zero otherwise. Includes days posted. MasculineJob$_S$ takes the value 1 if at least 80% of those who started an application for this job posting in the control were male (note members in both the control and the treatment apply to "MasculineJob$_S$" positions). MasculineJob$_F$ takes the value 1 if at least 80% of those who finished an application for this job in the control were male (note members in both the control and the treatment apply to "MasculineJob$_F$" positions). Legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

6.2 Survey

In June 2014 I administered an online survey to obtain insight into how job applicants perceive the number of 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 5–30 minutes.

Survey respondents were shown two almost identical job postings as pictured in Figure 7. The "BLUE" posting has no information and is the same as the control in the field experiment. The "PURPLE" shows the number of applicants; this number was randomly assigned to be 2, 26, 72, 273, or 4,124 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.

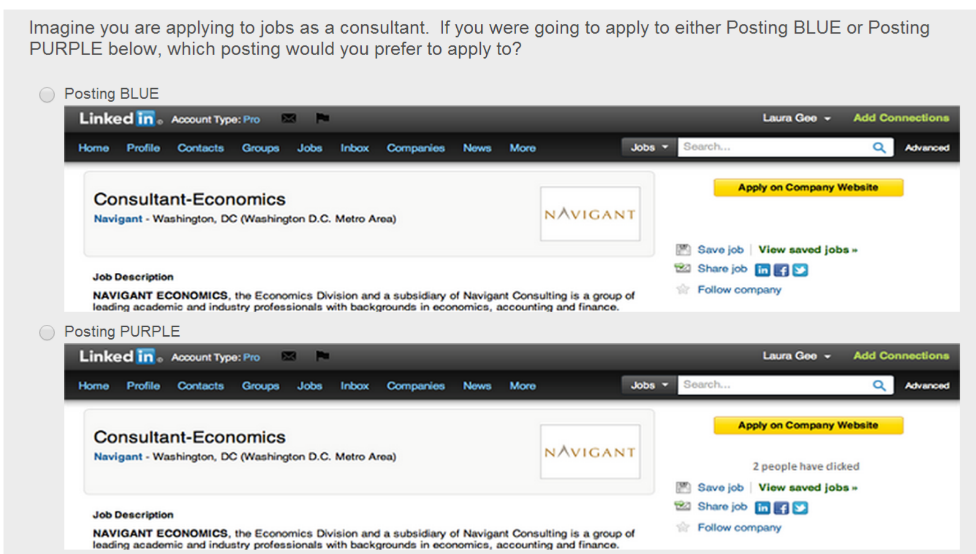


Figure 7: Type of Response by Number Seen

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

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 applicants. After making the choice between the BLUE and PURPLE posting, respondents were told, "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.[58] A research assistant was able to categorize 74 of the responses into one of the three

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

nonother categories. Interestingly, the respondents seem to interpret the same number (e.g., 2, 26, etc.) differently. For example, some believe that seeing two 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 8, which shows the proportion of respondents that interpreted the number shown as a sign of congestion/competition, signaling quality, or as extra useful information. Figure 8 shows that every number seen has a variety of interpretations, with the exception being 4,124, which the vast majority interpreted as a signal of congestion/competition.

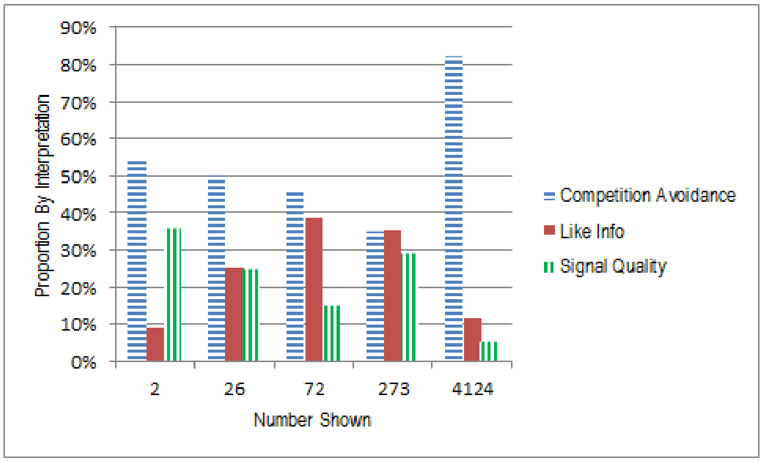


Figure 8: Jobs Landing Page

Note: This figure shows the proportion of respondents who interpreted the number of 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 applicants, either 2, 26, 72, 273, or 4,124. For example, for those who saw the number 26, 43% felt this signaled competition, 21% felt it signalled popularity, and 36% liked the additional information.

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 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 dropped. 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 9. The distribution is concentrated around "Very Likely" and "Likely" when only 10 applicants are seen, but shifts toward "Unlikely" and "Very Unlikely" when 100 applicants are seen. This result implies that as subjects see higher relative numbers they believe they face greater competition. This 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.

A final goal of the survey was to determine if people felt that the quality of the position was improving 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?

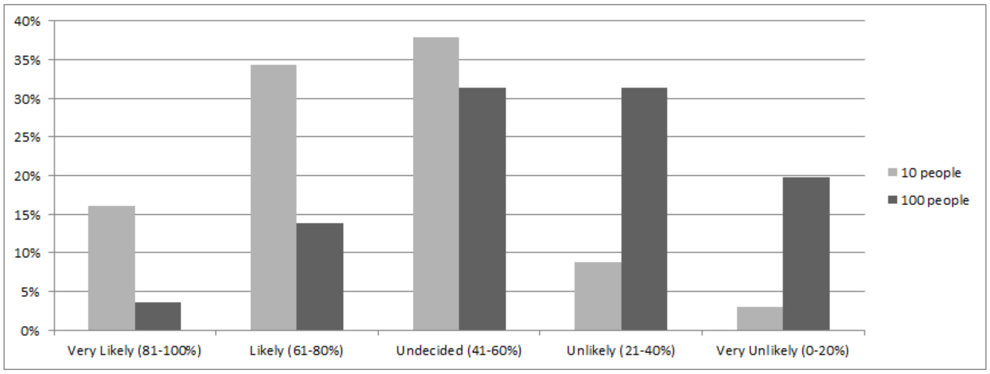


Figure 9: Likelihood of Job Offer

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 versus 100 applicants.

- 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 10. The proportion reporting they are “Very Likely” or “Likely” to enjoy the job is larger when 100 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 applicants shown rises. The shift in the distribution is similar for female and male respondents.

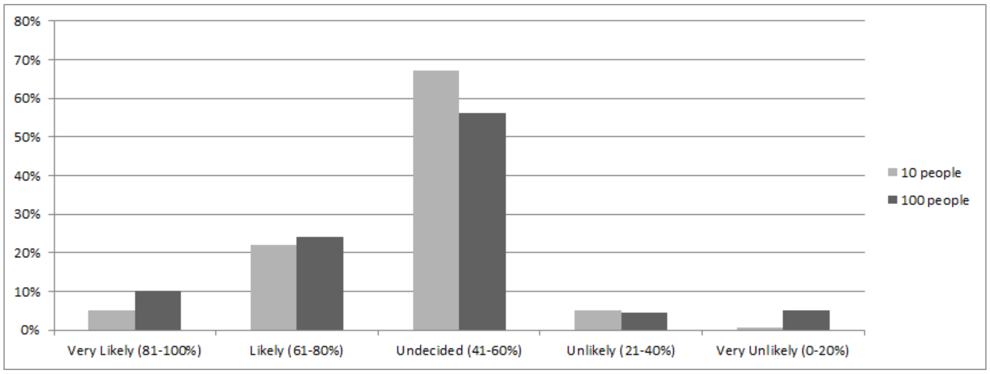


Figure 10: Likelihood of Liking Job

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

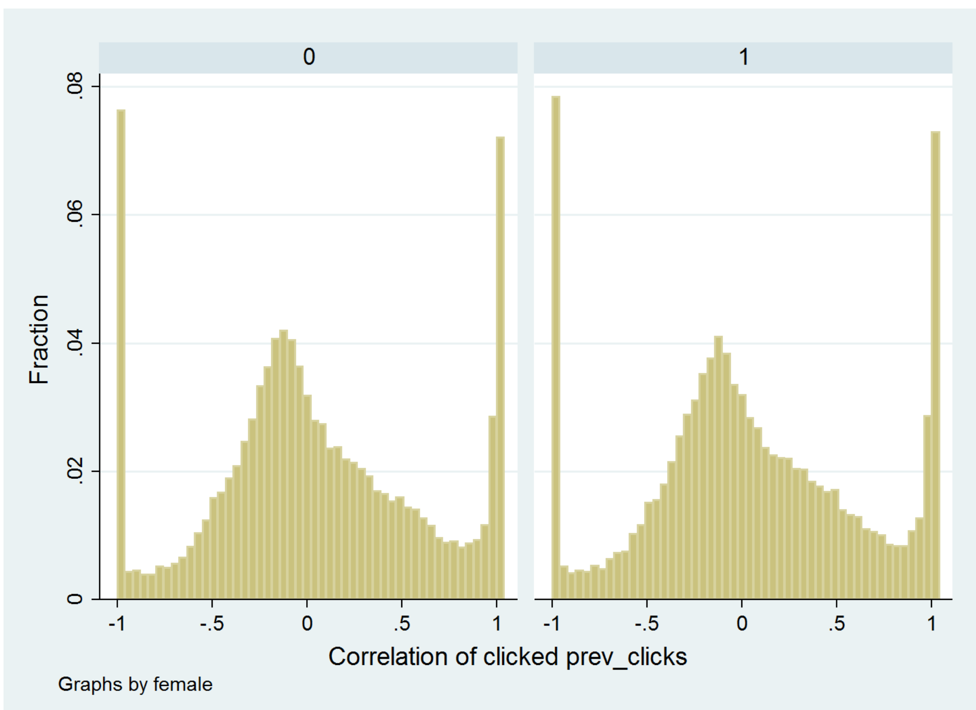


Figure 11: Distribution of Correlation Between Number Seen and Starting Application

Note: This figure shows the distribution of the correlation between number seen and starting an application for those in the treatment who have some variation in whether they apply (98,070). The left panel is for male job seekers and the right panel is for female job seekers. A correlation closer to -1 is evidence of competition aversion. A correlation of 1 is evidence of herding.

Figure 12: Average Correlation Between Number Seen and Start Application by Number Seen

Note: This figure shows the average correlation for all people who saw this specific number on a job posting. First, for each person in the treatment a correlation between number seen and starting application was computed. Then, for each number shown I find the average correlation for people who saw that number. So each dot on this graph represents an average of multiple user's correlations. For example, for the 35,251 users in the treatment who viewed a job posting with a 1 shown, the average correlation those users had was 0.05 (min: −1, max: 1). While for the single user who viewed a job posting with a 4,000 shown they had a −0.25 correlation. A correlation closer to −1 is evidence of competition aversion. A correlation of 1 is evidence of herding.