Social Learning with Congestion*

Monica Bhole
Facebook Research

Andrey Fradkin
Boston University

John Horton
MIT & NBER

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Abstract

We study how information about competition for a vacancy redirects applications. We conduct three experiments on a large online job platform in which treated searchers are shown information about the number of prior applicants to a vacancy. This information increases applications and redirects them to vacancies with few prior applications. Treated applications are more likely to be viewed by the employer. A complementary treatment shows that job seekers use the age of the vacancy to direct search towards newer vacancies. Information about vacancy competition directs applications towards older vacancies that would have otherwise been overlooked.

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1. Introduction

People use information about the behavior of others to make decisions about what to consume, where to apply, and how to search. For example, signals of song popularity (downloads) caused participants to download more popular songs (Salganik et al. (2006)). Herding behavior influenced by prior popularity signals has also been observed in social media, microlending, crowdfunding, and petitions (Muchnik et al. (2013), Zhang and Liu (2012)). People may follow signals of popularity for a variety of reasons, including because these signals contain information about the quality of an option. However, in labor, housing, and other constrained markets, popularity is also correlated with the degree of competition. More competitive options have a lower likelihood of success because the number of slots is fixed. This creates a tradeoff for individuals - apply to a more popular option but have a lower chance of success.

Platform designers must choose whether and how to display signals of popularity and competition information to its users, and this decision critically depends on how users perceive that information. The provision of information may improve market efficiency if it causes searchers to redirect applications to less competitive options, as predicted by some models of search (Wright et al., 2019). It may also improve market efficiency if it directs users to higher quality options. On the other hand, popularity information may be harmful to users if it induces herding and results in wasted search. However, which of these effects dominates is unknown, and major job search platforms differ in their information designs.[1]

We investigate how job seekers use information that simultaneously conveys vacancy popularity and competition in the labor market. We find that, when given information of the number of prior applicants to a vacancy, job seekers redirect their search towards vacancies with few prior applications. In a related treatment, we find that job seekers prefer recently posted jobs to jobs that are on the platform for a longer duration. Our main results demonstrate that participants in the labor market prefer to avoid competition even if it means applying to less popular jobs.

To conduct our study, we use three experiments encompassing millions of job seekers conducted on an online job board. We find that information about the vacancy level degree of competition affects job search, and in particular, directs applications towards vacancies with few applications in line with the spirit of directed search models. The applications induced by the information do not fully crowd out other applications and exhibit similar outcomes to

[1]As of 2022, Indeed and Google Jobs do not display the number of other applications on the search page while LinkedIn does. AngelList Jobs does not display the number of prior applicants but does display that the employer is actively hiring. All platforms display vacancy age, but the EconJobMarket also displays the deadline for applications.

those in the control group. We corroborate the results of our experiment with a choice survey taken by Mechanical Turk participants.

The setting of our study is a job board operated by Facebook called 'Jobs on Facebook' (JOF) until 2022. JOF was global, and mainly catered to full-time positions that did not require a college education. Users of the platform saw a list of vacancies and had access to a rich set of filters by which to refine their search. Searchers had the ability to apply to most vacancies using the platform. Consequently, the platform was also able to directly observe the number of applications sent to a particular vacancy in real-time and to display information about the count of prior applications to searchers.

We begin the paper by documenting three motivating facts. First, we show that being an earlier applicant increases the likelihood that an application is viewed, responded to by an employer, and results in an interview. Second, we show that applications to recently posted vacancies experience higher employer response rates. Third, we show that the number of applications received by a vacancy is highly correlated with the frequency with which it is shown to job seekers. This could be induced by the preferences of job-seekers, but it also suggests a role by the platform in which jobs it tends to promote—a factor that job-seekers might find it difficult to condition upon when searching.

Based on the above facts, we propose a simple theoretical framework for a job seeker's choice of whether to apply for a vacancy or not. In this model, information can affect two components of the seeker's choice, beliefs about job quality and beliefs about the likelihood of getting the job conditional on applying. Whether a particular piece of information increases or decreases application rates depends on how it affects these two components and is the empirical question we try to answer with our experiments.

Starting in March 2019 and continuing through August of 2019, Facebook conducted three experiments. All three experiments contained treatment arms that displayed information about the number of prior applicants to a vacancy in the search interface. The different treatment arms and experiments varied the frequency (every vacancy, every three vacancies, or every 10 vacancies) and color (grey vs blue) of the information.

We find that these treatments increase applications to vacancies with fewer than 5 applications by 3.8%, with a range of .9% to 6.4% depending on the experiment. In contrast, applications to vacancies with many applications fall. We also find that the total number of application increases due to the treatment. Therefore, the additional applications to low competition vacancies do not fully crowd out existing applications. The frequency and the color of information did not have first order effects on the rate of applications to these vacancies.

Next, we consider the role of vacancy age in directing job searchers towards less congested vacancies. In our experiment, vacancy age was always visible on the platform in our control groups. Vacancy age is positively correlated with the number of applications. As such, it is potentially a proxy for congestion and is available to job-seekers in many online settings. It also is informative about the probability that the employer has already made a decision, and thus whether an application is worth sending. In contrast to our other treatments in which the platform added signals to help direct search, removing vacancy age potentially removed a signal that otherwise could be used to direct search. But removing vacancy age helps us better understand what job-seekers were trying to accomplish.

We first show that vacancy age has an effect on the likelihood that an employer views an application, even conditional on the number of prior applications. As a consequence, searchers should attend to vacancy age when choosing whether to apply. Second, we show that workers use vacancy age to decide where to apply. We find that job seekers who do not have information about vacancy age clicked on 3% fewer vacancies and sent 1.8% fewer applications. This treatment also has distributional effects. Treated users were less likely to apply to new vacancies and were more likely to apply to old vacancies. Since vacancy age is correlated with the amount of competition for a vacancy, we find that removing vacancy age increases the concentration of applications. Furthermore, information about vacancy competition increases applications precisely to older vacancies.

Lastly, we study the causal effect of the treatment on the success and quality of applications submitted. On the one hand, applications in the treatment group should benefit from being earlier. On the other hand, searchers may choose to send these applications to worse matching vacancies which would then have a lower likelihood of resulting in a hire. As a result, the sign of effect of the treatment on application outcomes is theoretically ambiguous. We find that applications in the treatment were .02% more likely to be viewed by an employer. We also examine whether treated applications were contacted or interviewed through the platform. We do not have the power to precisely estimate similarly sized effects as for views, but can exclude negative effects smaller in magnitude than $.X\%$. This suggests that treated applications benefits from increased employer attention and that any negative selection of applications in the treatment was not large.

We do not find that behavior in the job market exhibits the type of social contagion based on popularity signals found in other digital settings (Salganik et al. (2006), Muchnik et al. (2013)). In other words, there is no danger of indicating a job is "popular" causing it to receive even more applications, as in some kind of social learning or information cascade scenario. In short, job-seekers view the application process more as a congestion game and all else equal, would prefer facing fewer competitors.

Our results provide causal evidence about platform generated signals that can direct search. The effects of these signals show that workers try to avoid applying to vacancies with a high level of competition. These signals correspond to a common feature of directed search models that workers care about the likelihood that their application is succesful (Wright et al. (2019)). Cheron and Decreuse (2017) and Albrecht et al. (2017) focus specifically on the importance of 'phantom vacancies', which are vacancies that have already been filled. In their models, workers rationally direct search towards newer postings—a phenomenon which we document empirically and confirm using experimental variation regarding information about vacancy age.

Other papers in the literature have shown that search is directed on many vacancy characteristics such as compensation (Belot et al. (2018), Banfi and Villena-Roldan (2019), Flory et al. (2015), Samek (2019)) and signals of employer preferences (Kuhn et al. (2018), Leibbrandt and List (2018), Ibañez and Riener (2018)). A particular focus of this literature has been gender differences in preferences regarding the competitiveness of compensation schemes. We study a different aspect of competitiveness, which is the amount of competition to get hired. We are not able to detect differences between men and women regarding their preferences towards such jobs.

Our treatments are enabled by the fact that digital job boards have a bird's eye view of the market. While this may seemingly limit the applicability of this approach, given that the labor market as a whole is decentralized, an increasing amount of job search occurs on digital job boards (Kuhn and Mansour, 2014; Baker and Fradkin, 2017; Kroft and Pope, 2014; Marinescu, 2017). These job boards make decisions that could ameliorate—or worsen—congestion. Due to the heterogeneity in preferences for vacancies-across seekers and vacancies, centralized matching is infeasible. Instead, the platform can influence matching indirectly through the information it chooses to display and emphasize.

We build on the paper by Gee (2019), who varied whether the number of 'people who clicked to apply' to a vacancy was shown on LinkedIn. A critical difference between our work and Gee's is that our experiment is conducted a different point in the job application "funnel." In our setting, job-seekers can scan over a collection of jobs and learn about the relative degree of competition, whereas in Gee (2019), they only learn about competition after choosing to investigate a particular job.

The timing of information acquisition has previously been shown to matter greatly for outcomes in search markets (Branco et al. (2012); Hodgson and Lewis (2020); Gardete and Hunter (2020); Abaluck and Compiani (2020)). This is the likely reason that we find that applications increase for vacancies with few prior applicants and decrease for vacancies with many applicants while Gee (2019) does not. When comparing other outcomes, Gee (2019) finds that applications per view increase and overall applications increase by 3.7%. In comparison, we find that applications increase by less than 1% but that applications per detailed view increase by a similar amount as in Gee (2019). Although the timing of information acquisition is a key detail, there are also other differences between our paper and that of Gee (2019) that may contribute to any differences in findings. In particular, our sample tends to be less educated and less likely to be non-US based (42% US based in Gee (2019) vs 20% to 27% in our experiments).

Several other papers have used data on search in digital labor platforms. Faberman and Kudlyak (2019); Marinescu (2017) study how search evolves over the course of an unemployment spell, Marinescu (2017); Marinescu and Skandalis (2019); Baker and Fradkin (2017) study how unemployment insurance affects online job search. Azar et al. (2019) use data from CareerBuilder to build a demand model of applications and use it to estimate firms' market power in the labor market. Le Barbanchon et al. (2020) use data on search criteria declared to a public employment agency, as well as applications on a digital platform, to show that women care more than men about commuting when it comes to applying for jobs. Skandalis (2018) shows how job search is affected by news about a company's hiring needs.

The above literature has not focused on the market design possibilities available on job boards. Our paper shows that the information design of these job boards has large effects on behavior. This creates opportunities for additional information interventions, and the study of their equilibrium effects using market level experiments. In this way, the market design innovations pioneered in other digital platforms, such as those for labor procurement (Horton (2017)), dating (Fong (2019)) and accommodations (Fradkin (2017)), can be used to improve outcomes on digital job boards. More recently, Hensvik et al. (2020) have studied the effect of algorithmic recommendations in a job board similar to ours.

The rest of the paper is organized as follows. Section 2 describes the empirical context. Section 3 presents a decision framework and stylized facts that motivate our experimental treatments. Section 4 discusses the design of our various interventions. Section 5 reports the effects of the treatment on search behavior. Section 6 discusses the our results with respect to vacancy age. Section 7 reports on the differences between applications across treatments. Section 8 concludes.

2. Empirical context

JOF is an online job board that was launched in the US in 2016 and then worldwide in October 2018. The product is global in nature and mainly caters to positions which do not require a college education. The share of US users across our experiments ranged from 21% to 25%, and the median user in our experiments was between 31 and 33 years old across experiments.[2] Employers can post vacancies and job-seekers can browse vacancies and send applications through the platform. The service is free for both sides, but job-seekers must have a Facebook account. A posted vacancy is automatically live for 30 days, but employers can renew it. This results in an average duration during our testing period of 42 days.[3] Even before the launch of JOF, there was substantial job-search behavior on Facebook (Gee et al., 2017).

Job-seekers are exposed to JOF via the "News Feed" and via notifications.[4] They can also navigate to JOF by clicking on the "Explore" tab and then clicking on a briefcase icon labeled "Jobs." The JOF interface is similar to other job boards, though most of job search occurs on mobile devices. That most use occurs on mobile presents opportunities—if the user has enabled location-tracking, vacancies within a given radius can easily be shown—but also challenges, in that there is a constrained space in which to present information.

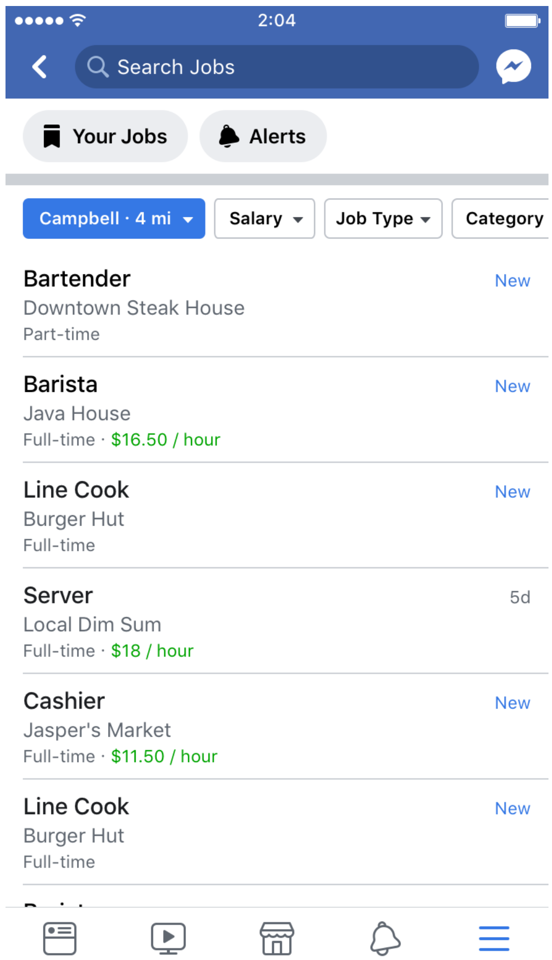
When looking for work, job-seekers can enter a number of criteria to narrow their search, including their location and the type of position they are interested in. Figure 1 shows the *status quo* job search interface (the job board)—as we will discuss at length, this presentation was modified by various treatments. As we can see in the figure, for each vacancy, the job-seeker can see the title of the job, whether it is part-time or full-time, the name of the employer, number of days since it was posted, and if the employer has posted the wage, the hourly wage. To learn more about the vacancy, the job-seeker has to click on the "tile" for that opening. Clicking exposes a "detailed view" of the job that includes the full job description written by the employer. It also includes an "apply" button that the job-seeker can use to submit an application.

[2]According to publicly available data, approximately 10% of Facebook's overall user base is based in the United States. JOF's relatively high penetration in the US is likely due to the fact that JOF first launched in the US prior to being expanded globally (https://perma.cc/6CAM-EKLR).

[3]We calculate this duration for all vacancies created between March 2019 and August 2019. Note that Facebook reviews job postings and may remove them from the platform prior to the scheduled expiration of the job. Therefore, this number is an overestimate of the length of time that a job may be visible on the platform.

[4]Which users are exposed to the Jobs product in the News Feed is determined by an algorithmic system and is not dependent on the treatment assignment of the experiments discussed in this paper.

Figure 1: *Status quo* job search interface for Jobs on Facebook job-seekers



Notes: Interface shown to job-seekers on a mobile device.

2.1 Measurement of job-search behavior

We observe the job vacancies a user loaded onto the job board during their search, which is a function of how far they scrolled down the device, their location, and their search query parameters. A "view" occurs when a vacancy appears on a screen. We also observe whether the user clicked on a vacancy to learn more, which we call a "detailed view." Finally, we observe whether the job-seeker applied to a particular opening and some information about that application.

When job-seekers start an application, information about them is populated into an application, using data from their Facebook profile—educational history, past employment, contact information and so on. Searchers can fill in additional information that is not already listed on Facebook. Our application measure is likely a lower bound on the number of job applications created, as in some cases, job-seekers would have enough information about the employer to apply directly.[5] However, the convenience of simply submitting through the Facebook App makes this the most likely course of action.

After an application occurs, we have imperfect information about what happened. For vacancies created through the JOF platform, which we call 'native', we can observe a variety of interactions including whether an employer viewed an application, whether the employer contacted an applicant through Facebook, and whether an employer told Facebook whether an interview was scheduled. Each step in this process is 'leaky', so that we see a large share of applications are viewed, but a much smaller share have contacts and interviews. This partially occurs because at each step employers and applicants can choose to take the interaction off of the platform. There are also vacancies which are syndicated from other platforms, which we refer to as 'third-party vacancies'. In the US, third party platforms can be applicant tracking systems. For some of these vacancies, we cannot measure interactions between applicant and employer because the interactions take place off of the platform.

3. Theory and evidence on the role of application order and vacancy age.

Job platforms are interested in helping their users find good matches. As part of this goal, they provide information to users in order to help them form these matches. In this section we describe a simple decision framework for what job seekers *should* care about. We then

[5] There are some vacancies which do not allow the user to apply using the Facebook platform. These vacancies are syndicated from outside of JoF. We do not include these in our calculations of application rates.

document three empirical regularities which motivate our experimental analysis of information about prior applications and vacancy age. These three regularaties are, first, that earlier applicants have a higher likelihood to have their applications viewed and responded to. Second, even conditional on the number of applications, applications sent to more recently posted vacancies are more likely to get a response. Lastly, the imbalance in vacancy popularity coincides with an imbalance in the likelihood that a vacancy is exposed to users in search. The advantages of applying earlier combined with imbalances in applications across vacancies point to a role of information interventions, which we discuss in the next section.

3.1 Decision Framework

Job seekers would like to obtain the job that gives them the highest utility, which may stem from wages and other amenities. However, some jobs that would give a high utility cannot be obtained. This could be because the employer judges the worker unqualified for the job, because the competition for the job is too high, or because the employer has already interviewed the candidates who will be hired. Given these concerns, job seekers value information about the likeihood of obtaining a job in addition to the quality of the job.

Suppose job seekers enter the market at time t, evaluate jobs sequentially, and apply to a job if their expected benefit from applying exceeds the costs. Let a job seeker's expected utility from a job offer from vacancy j be $u_{sjt}(z_j, x_j, s_{tj})$. This expected utility is a function of the job characteristics, x_j, searcher characteristics, z_i, and information, s_{tj} about the vacany's status at time t. Similary, let a job seeker's belief about receiving and accepting an offer be $b(O_{sjt}(z_j, x_j, s_{tj}$. The job seeker applies to vacancy j if:

$$b(O_{sjt}(z_j, x_j, s_{tj} * u_{sjt}(z_j, x_j, s_{tj}) > c(n) \tag{1}$$

Note that the cost of applying $c(n_s)$ may vary with the amount of prior applications sent by the searcher (n_s). Ursu et al. (2022) show that consumers get tired or distracted from searching and that this rationalizes costs that increase in the amount of time spent searching.

We are interested in understanding how signals about a vacancy observed by platforms, such as the amount of competition and the age of the vacancy affect the decision to apply. As we show in the next several sections, vacancies that have already received many applications are less likely to interview and hire new applicants. Similary, vacancies that have been posted a longer time ago are less likely to inteview and hire. These stylized facts suggest that providing meta-information will lead job seekers to update their beliefs about an offer. As a result they should direct search effort to younger vacancies with few job applications.

In contrast, it could be that the number of prior applications is indicative of a higher utility job. For example, the fact that many others have applied could mean that those others have read the detailed job description and have found it appealing. Or that they know something about the employer that makes the application a particularly high value. In that case, information that a vacancy has many applications could actually increase the likelihood that job seekers apply.

3.2 Effects of applying earlier

We now show that applying earlier (whether measured by the application order or time) results in a higher probability that an application receives a positive outcome. The simplest explanation for this is that an employer checks applications at some time that the applicants cannot condition on. As a result, when everything else is held constant, earlier applications are more likely to be considered. However, it is possible that better applicants apply more quickly, which could create the illusory appearance of application rank mattering, and so we have to be cautious in claiming a true causal effect.

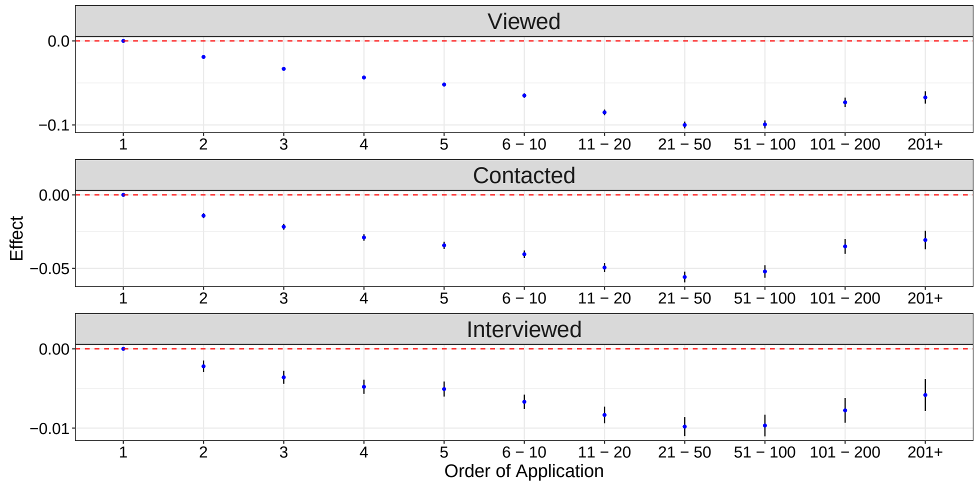
To measure the effect of application order, we can compare the outcomes of multiple applications to the same vacancy. In particular, we estimate regressions of the following form:

$$y_{ij} = \beta_{\text{order},ij} + \delta_{\text{age},ij} + \kappa_j + \epsilon_{ij} \tag{2}$$

where y_{ij} are application outcomes for vacancy j by application i, $\beta_{\text{order},ij}$ are fixed effects for the order of the application (e.g. 1st application, 10th application), $\delta_{\text{age},j}$ are fixed effects for the age of the vacancy at the time (e.g. 1 day, 3 days) at which the application was submitted, and κ_j are vacancy fixed effects. We estimate the above equation on a 5% sample of vacancies posted between March 3 and August 18 of 2019, the period during which our experiments ran.

Figure 2 displays the estimated coefficients on application order from the above equation, where the first application is normalized to 0. Later applications have a lower probability of being viewed, contacted, and interviewed. To get a sense of the magnitudes involved, the baseline rate of interviews in this sample is 1.3%, which reflects the fact that many employers do not use the JOF interface to record interviews.[6] We see that later applications experience an over 65% decline in interview rates for these employers. Note that there is some monotonicity in our estimated effects as the application number exceeds 100. This is likely due to the fact that not every vacancy achieves over 100 applications, and that, as a result, the composition of vacancies is also changing with the application number. To summarize, application order matters for application outcomes, and this justifies our focus on providing application order

Figure 2: Relationship between application order on employer responses



Notes: Each point represents the estimated effect and each line present the 95% confidence interval for estimates of the effects of application order on whether an application is viewed, responded to, or results in an interview. The coefficient on the first application is normalized to 0. Standard errors are clustered at a vacancy level.

information to job-seekers.

A related question is whether and how job-seekers know about the negative relationship between application order and interview rates. This relationship is likely to hold for most vacancies, regardless of platform, so that anyone who's searched for a job before may have had a chance to learn about it. Furthermore, many people have been on the hiring side of the market and could have observed that earlier applications get more attention. Lastly, people looking for advice online will find advice suggesting that earlier applications are more likely to be successful.[7]

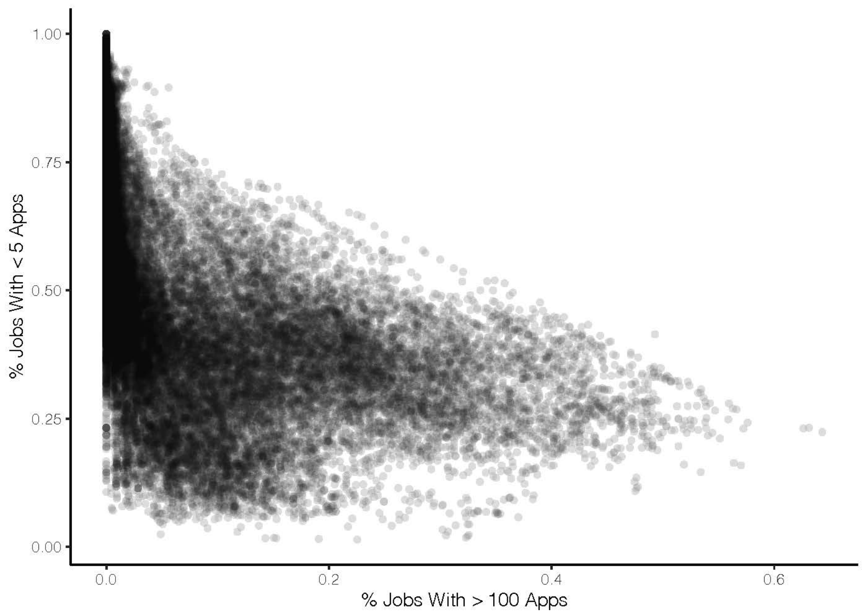
3.3 Imbalances across vacancies

To measure outcomes at a more aggregate level, we need an appropriate definition of a market, which for labor markets is typically a commuting zone (CZ). We use a global mapping of locations to CZs based on location data, which is constructed by Facebook (Facebook (2020)). There are also alternative definitions of labor markets based on occupational definitions (e.g. Modestino et al. (2020)) but we do not currently have access to data on occupation.

[6] Due to confidentiality reasons, the company did not want us to report the baseline rate of views and contacts in this sample. Table 2 displays regression results for a different sample in which the view rate in the control group is 57% and the contact rate is 38%.

[7] For example, see this Quora question: "Does it make a difference if you apply for a job as soon as it is posted?": https://www.quora.com/Does-it-make-a-difference-if-you-apply-for-a-job-as-soon-as-it-is-posted.

Figure 3: Prevalence of Under-subscribed vs Popular Vacancies by Commuting Zone - Week



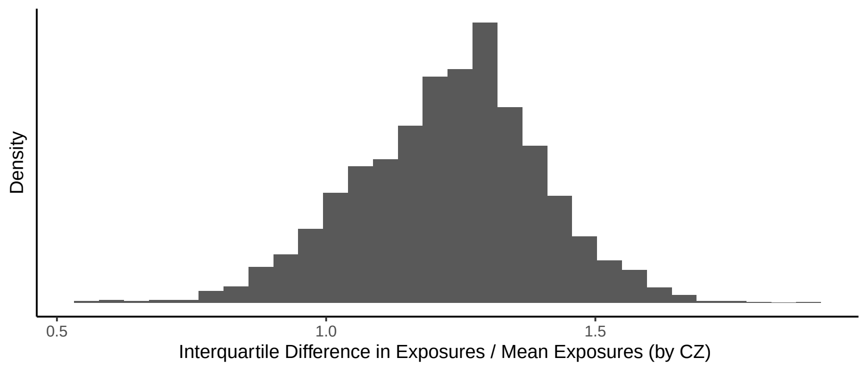
Notes: Each point plots the share of vacancies with more than 100 applications against the share of vacancies with fewer than 5 applications within a month of posting by commuting zone and week. The sample includes weeks between '2019-02-26' and '2019-09-01'. Only commuting zones with at least 100 posted vacancies are included.

In Figure 3, we plot the share of all vacancies in a given CZ-week that received fewer than 5 applications in the first month that it was open versus the share of all vacancies in a given CZ-week that received over 100 applications. The plot demonstrates that there is imbalance in applications across vacancies. Vacancies with many applications exist in the same commuting zones as vacancies with few applications. Of course, there are many factors that could explain this pattern that are not *per se* inefficient—job-seekers could be avoiding "bad" jobs and seeking out "good" jobs–but the general pattern is suggestive that there is an opportunity for a better distribution of applicants over vacancies.

The imbalance in applications coincides with the imbalance in the frequency with which vacancies are viewed by job seekers. We are able to calculate the number of views each vacancy received as well as the number of applications.

There is a correlation of 0.47 between the number of views a job has and the number of applications it has in this sample. This may reflect both the fact that some vacancies get exposed more due to their location in a place with many searchers, due to the fact that vacancies vary in other characteristics related to search, or due to ranking algorithms. Furthermore, since such algorithms learn from prior users, there may be reverse causality between applications

Figure 4: Imbalance in Views by Vacancy



Notes: Histogram of the share of normalized inter-quartile range of the number of views per job. The sample aggregates over all exposures between '2019-07-22' and '2019-08-18'. Only commuting zones with at least 100 posted vacancies are included.

and exposures.

Nonetheless, we find that the imbalance in applications across vacancies is also reflected in exposures. Figure 4 displays the inter-quartile range of exposures with a commuting zone normalized by mean exposures in that CZ. The difference in the inter-quartile range is typically greater than the mean number of views, and there is substantial variation across CZs. These facts regarding views and applications motivate our theoretical framework and experimental analysis.

4. Experimental provision of information

Our primary research interest is in how information about the competition for a particular vacancy affects job-seeker decision-making. We study this question by analyzing three experiments conducted over a five month span in 2019.[8] The authors of this paper provided input into the design of these experiments but these experiments were primarily conducted for the purposes of improving the JOF product. The final decisions regarding which treatment arms to run and when were determined by product managers and designers. When large samples are possible, it is common practice for tech companies to test many minor variants of a design (see Kohavi et al. (2020) for details about large-scale experimentation at technology companies).

The experiments all varied the information job-seekers had about a vacancy when they viewed it. In total, there were 17 treatment arms across the experiments. On platforms with

[8]Experiment I was conducted from 2019-03-26 to 2019-05-09 (44 days). Experiment II was conducted from 2019-05-31 to 2019-06-28 (28 days). Experiment III was conducted from 2019-07-22 to 2019-08-18 (27 days)

vast numbers of users, it is typical to try many variations of a treatment to determine the best one, given the amount of statistical power available. A randomly chosen subset of $\leq 50\%$ of job seekers were eligible for each of the experiments.[9] Across the experiments, treatment cells differed in (a) what information was displayed, (b) how spaced out the information was (with information only presented for a subset of tiles), (c) the color (grey vs blue) of the information (to make information more or less salient). Note that other aspects of Facebook's systems, such as the ranking algorithm, did not have a signal of treatment assignment.

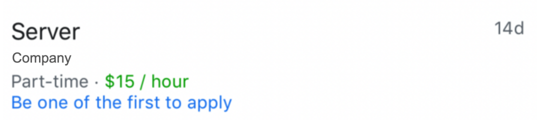
Figure 5 displays how the interface presented to job-seekers is altered by the treatments. Figure 5a displays one job tile when the number of applicants is less than 5. The color and the information varies depending on the treatment and the number of applications to the vacancy. Vacancies that have more than 4 prior applications have messages that display one of the following texts: '5 - 20 applications', '21 - 50 applications', '50 - 200 applications', '201+ applications'. Figure 5b displays the control tile. Note that the control tile occupies *less* vertical space than the treatment tile. This will be important for our subsequent results given the limited screen space available on mobile devices. Figure 5c displays how each tile is combined in the JOF product.

Given the number of treatments available, we primarily analyze the experiment by pooling similar treatment arms. This allows us to simplify the exposition and increase our statistical power. Appendix A demonstrates that the specific manner in which a particular intervention was implemented within an experiment was not of first order importance to the treatment effect on applications. This appendix also demonstrates that the experiments are balanced on pre-treatment covariates—indicative of a successful randomization.

One concern with our experimental design is that there may be violations of the Stable Unit Treatment Value Assumption (SUTVA). In particular, when a treated searcher applies to a vacancy due to the treatment, this may affect the competition faced by the control searchers and may affect the job posting behavior of employers who receive applications induced by the treatment. As a result, our experimental analysis focuses on the effects on differences in individual behavior under the market conditions faced by searchers during our experiments. We are not able to capture how the treatment affects the equilibrium level of competition and match rates on the platform.

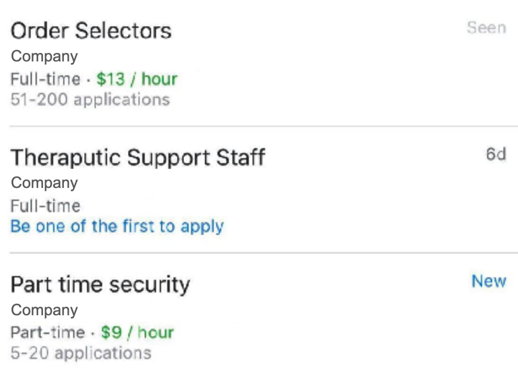
[9] Note that for reasons of confidentiality the company did not permit us to report the exact percentage. Tech companies often allocate only part of the universe of users for an experiment in order to isolate the effects of potentially interacting concurrent experiments and in order to mitigate risk (Bakshy et al. (2014)).

Figure 5: Illustration of popularity information shown vacancy tiles



(a) Notice on a job tile that a job has few applicants (in blue)

(b) Control presentation of a job tile



(c) Bin applicant count information

Notes: Job vacancy tile interfaces.

5. Effects of information about the number of prior applicants

Directly displaying information about the number of prior applicant increases applications and redistributes them towards relatively under-subscribed vacancies. The effect of the treatment on applications comes from information displayed about a particular vacancy.

5.1 Overall job application intensity

We begin by analyzing the aggregate job search effects of the pooled treatment before discussing its heterogeneous effects across vacancies. We estimate these effects by running regressions of the following form:

$$Y_s = \gamma_{exp} + \beta_1 Treat_s + \epsilon_s \tag{3}$$

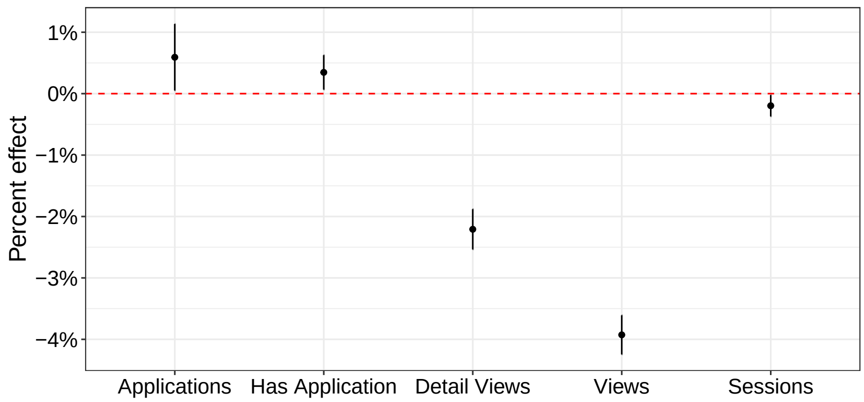
where Y_s refers to outcomes for searcher s observed in the experiment and $Treat_s$ refers to an indicator variable for whether the searcher was in the treatment group that provided information on the number of prior applicants. We also include fixed effects, γ_{exp} for the experiment number (1 - 3). To get an effect in terms of percents, we take a ratio of β_1 and the mean of Y in the control group. Figure 6 plots the treatment effects for the main variables of interest calculated across from the pooled sample consisting of 29,375,533 observations.[10]

Total applications increase by 0.59% and the share of searchers with at least one applications increases by 0.35%. This demonstrates that the treatment effects are coming from both the extensive and the intensive margin. In contrast to the effect on total applications, we find relatively large decreases in the number of views and detail views. These decreases in views are mostly a mechanical consequence of the fact that the information provided by the treatment takes up more space in the interface.[11] In Appendix A, we demonstrate this fact by showing that the treatment effect size is correlated with how frequently information is shown in a given treatment. The effect on the number of search sessions is less pronounced at -0.2%, which may explain why we nonetheless see increases in overall applications.

[10] Standard errors for this object are calculated via the delta method. We considered using randomization inference but the computational costs were high with our large sample size and the bias of the asymptotic standard errors is likely to be low with a large sample.

[11] To see that the negative effect on views is plausible, suppose that a mobile phone screen can fit four vacancies on average, and that each vacancy takes up three lines without the treatment. Adding one extra line takes up an extra $1 - (4 * 3)/(4 * 3 + 1) = 7.7\%$ space. Given the diversity of mobile phones and differences in search activity, it is plausible that this extra line can affect whether a vacancy is viewed.

Figure 6: Effects of revealing congestion information on job search behavior and outcomes



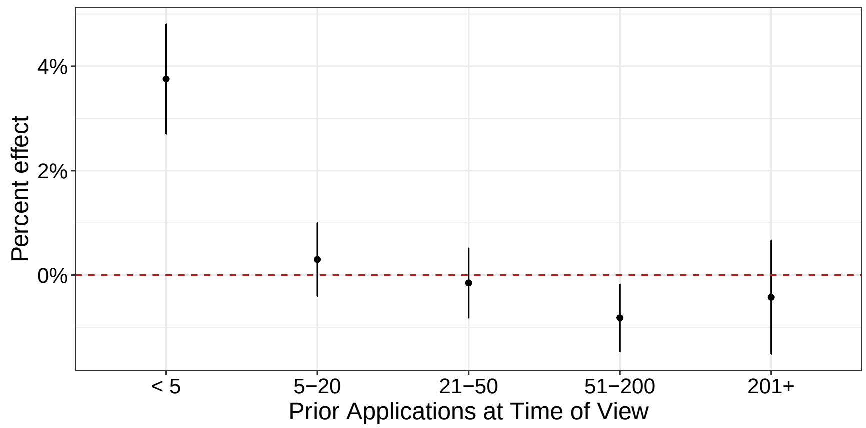
Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. Each observation is a searcher in an experiment and all treatments that included information about prior applications were pooled. Standard errors are computed via the delta method.

5.2 Redirection of applications to vacancies with fewer prior applicants

The largest increases in applications occur for vacancies with few prior applications and there are negative treatment effects for vacancies with many prior applications. To show this, we estimate equation Equation 3 with the outcome, Y_i, equal to the number of applications sent by seeker i to jobs with a number of applications at time of exposure in a particular range. We bin outcomes in a way that parallels the information treatment. Figure 7 displays the results. We find positive treatment effects for applications to vacancies with fewer than 5 prior applications. We find negative treatment effects for vacancies with more than 20 applications and in the case of the 51 - 200 prior applications bin, this effect is statistically significant. This is consistent with out theoretical framework, which predicts a redistribution of applications from vacancies that get many applications to those who get few applications. In, Figure B.3, we investigate heterogeneity by a number of factors including gender, age, and device and fail to detect statistically significant differences.

A striking pattern in Figure 7 is that the effect on applications is largest for vacancies with fewer than five applications. This could be due to the fact that the information is displayed as ‘Be one of the first to apply’, which makes the amount of competition especially salient or due to nonlinearity in searchers’ utility functions with regards to competition. This effect is not driven by the frequency with which information is shown or by whether information about other application bins is shown. Figure A.6 shows that the effect on the < 5 category

Figure 7: Effects of congestion information on applications to different status vacancies



Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. Each observation is a searcher in an experiment and all treatments that included information about prior applications were pooled. For each searcher, we observe the number of applications in the experiment sent to jobs with a number of prior applications in a given bin. This calculation is done at the time the seeker is first exposed to a particular vacancy. Standard errors are computed via the delta method.

is similarly sized for 7 different treatment arms and is larger than the overall average effect.

Conditional on viewing a vacancy, treatment users are more likely to click on the vacancy and apply to it. Figure 8 shows that this effect is especially large for vacancies with fewer than 5 prior applications. This supports our theory that searchers prefer vacancies that have few applications.[12] We also find that vacancies with fewer prior applications experience greater increases in detail views per view. This provides evidence that the information is helping searchers direct their search by clicking on vacancies with fewer prior applications.

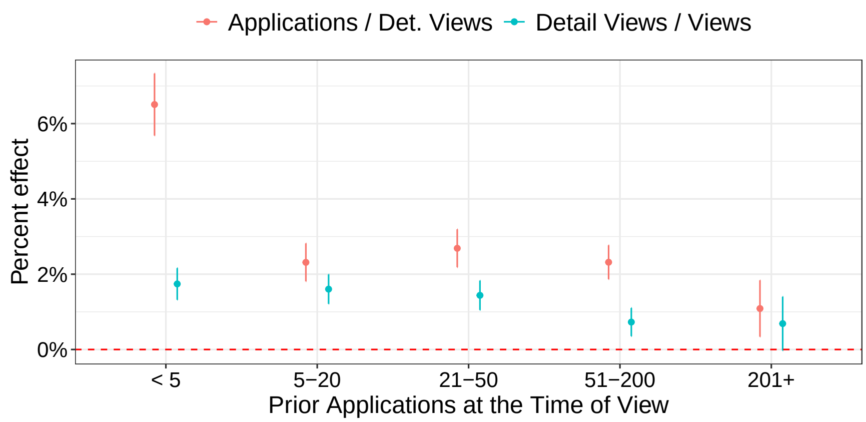
The evidence regarding applications per detailed view also allows us to make a closer comparison to the work of Gee (2019), which focuses on this outcome metric. Gee (2019) finds that her information treatment increases applications per view by 3.5% but that that effect does not vary by the exact infromation shown. Our estimates in Figure 8 show similar effect sizes ranging from $> 6\%$ to $< 1\%$, which depend on the exact information shown.

5.3 Spillovers

Finally, we consider whether the effect of the treatment comes solely from the information about a particular vacancy or whether there are spillovers onto vacancies for which no information is provided. A positive signal about a particular vacancy may draw away applications

[12] The overall increase in the treatment ratios can be explained by the fact that the treatment reduced views and detail views.

Figure 8: Effects on detail views / views by prior applications to a vacancy

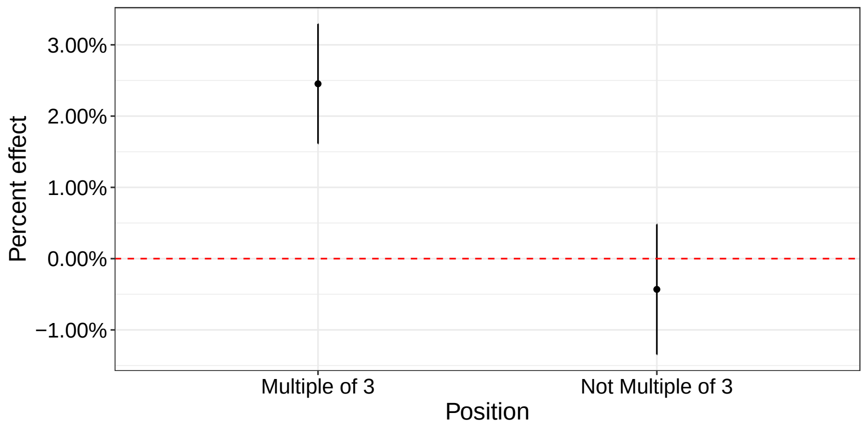


Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. The outcome is the ratio of detail views to views. Each observation is a searcher in an experiment with at least one view or detail view for a job in the bin and all treatments that included information about prior applications were pooled. Standard errors are computed via the delta method.

from other vacancies or it may induce additional applications to other positions due to learning. We can study these mechanisms by considering treatments which display information every three tiles rather than every tile. If information causes substitution, then we should see that the treatment has negative effects on vacancies that appear on tiles that are not multiples of three. On the other hand, if there is learning, we should see positive effects for these tiles.

Figure 9 plots the treatment effects on applications based on the position in which they were shown. The estimates are pooled across two treatment arms for which information is displayed every third tile and only when the vacancy has fewer than five applications. We see a positive and statistically significant effect for vacancies in a position divisible by 3. In contrast, for vacancies in other positions, we see a negative but small in magnitude and insignificant effect. This coefficient is consistent with some level of negative spillovers between ads with and without information, although if we take the point estimates at face value, then the negative spillovers on the two positions without information (2*.5%) are smaller than the positive effect on the vacancy with the information (2.5%). As a result, it's likely that the applications induced by the treatment come from the information learned about particular vacancies and that negative spillovers to other vacancies do not wholly outweigh the benefits to the treated vacancy.

Figure 9: Effects of congestion information on applications, by position of vacancy



Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. The outcome is the number of applications. Each observation is a searcher in a treatment arm where information is displayed every 3 tiles or in the control. Standard errors are computed via the delta method.

6. Vacancy age effects

In conventional job markets, job-seekers can potentially know the age of a vacancy because it is provided directly by the platform. To understand how this information is used, we show how job-seekers without access to this vacancy age information responded.

Before we present these results, it is useful to step back and consider what we know from the other cells. To summarize, we have shown that job seekers value information about the level of competition when applying for vacancies and respond by applying to vacancies with fewer prior applications. We now investigate whether searchers use other information as a proxy for vacancy competition.

We find that job searchers use the vacancy age as a proxy for competition when other information is not available and that, when vacancy age information exists, competition information helps to attract applicants to older vacancies.

We begin by showing that vacancy age affects the probability of responses from employers. To measure this, we plot the estimated coefficients for vacancy age from Equation 2 in Figure 10, which include vacancy fixed effects and application order controls. We find that, even conditional on the order of the application, vacancy age is negatively correlated with employer responses, whether these are measured by views, contacts, or interviews. Although the coefficients are not as large in magnitude as those we found for application order, they are nonetheless statistically significant.

Figure 10: Relationship between vacancy age at the time of application and employer responses

Notes: Each point represents the estimated effect and each line represents the 95% confidence interval for estimates of the effects of vacancy age at the time of application on whether an application is viewed, responded to, or results in an interview. The coefficient on the first application is normalized to 0. Standard errors clustered at a vacancy level.

Given that searchers should care about vacancy age, we now study what happens when vacancy age is not displayed but everything else is held constant. This was the case in one treatment arm of Experiment I. In the control group, the tile displayed 'New' in blue if the vacancy was 5 or fewer days old, and would display 'xd' in grey otherwise, where 'x' is the number of days the vacancy has been posted (See Figure 1).

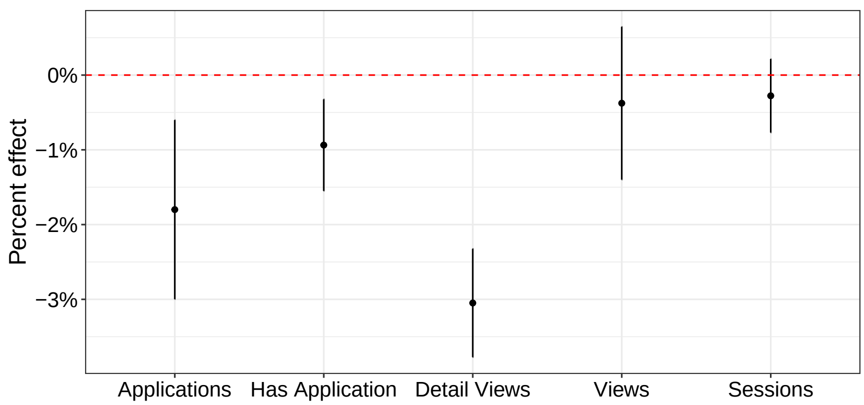
Figure 11 displays the overall effects of removing vacancy age. We see that treated users submitted fewer applications and clicked on fewer vacancies. These effects are of comparable magnitude to the effects of including information on prior applicants. Consequently, searchers are using vacancy age to choose to use the platform and to direct their search.

We investigate these effects further by calculating the treatment effects based on the age of the vacancy at the time of the view. The left panel of Figure 12 displays the treatment effects split by whether the vacancy had the text 'New' or not. We see that removing vacancy age decreased applications and detail views to new vacancies and increased them for vacancies older than five days. This heterogeneous effect suggests that users prefer applying to new vacancies when both new and old vacancies are identifiable, but otherwise cannot perfectly predict vacancy age based on observed information.[13]

Since vacancy age is correlated with the number of prior applications, we consider whether

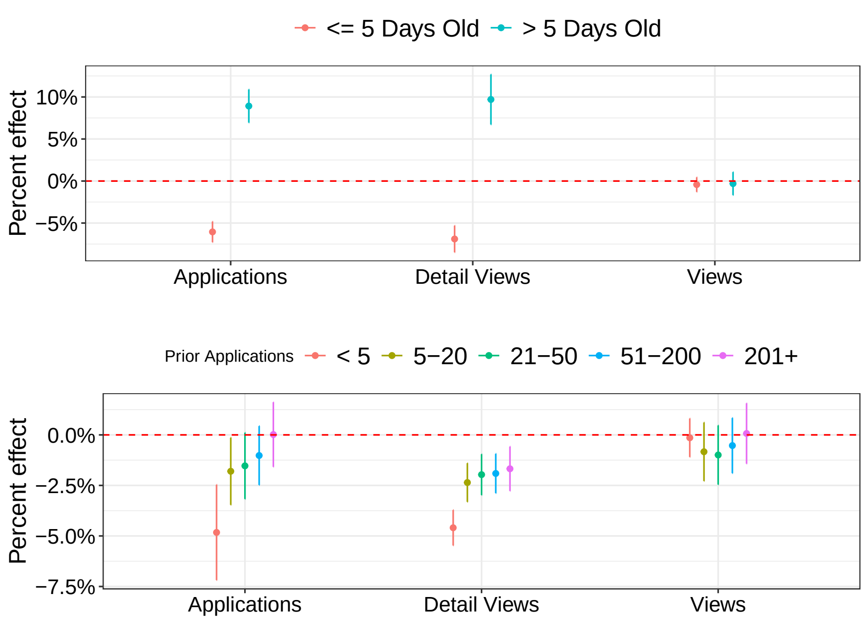
[13]Seekers may also try to infer vacancy age from other job characteristics or the ranking of the result. In this sense, our estimates represent a lower bound on the effects of vacancy age on search.

Figure 11: Treatment effects on job search outcome
Removing vacancy age



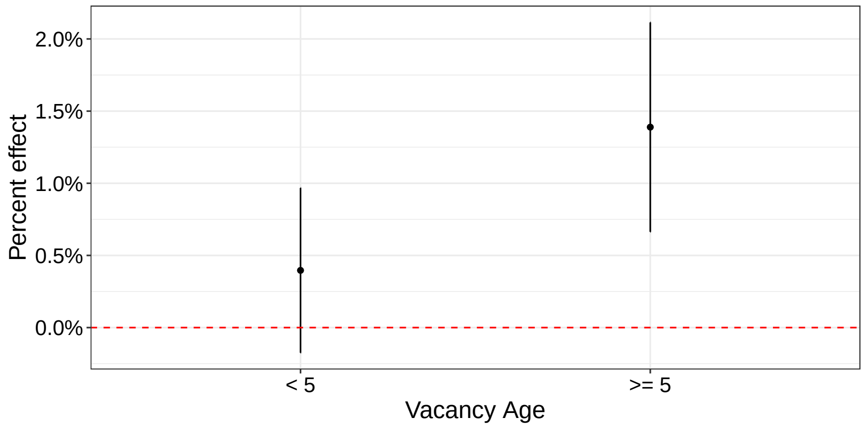
Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. Each observation is a searcher in experiment I who was either in the control group or in the treatment group for which vacancy age was removed.

Figure 12: Treatment effects by job type
Removing vacancy age



Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. Each observation is a searcher in experiment I who was either in the control group or in the treatment group for which vacancy age was removed.

Figure 13: Treatment effects on vacancy age of applications
Competition information



Notes: This figure plots the average effects in percent terms and their 95% confidence intervals. Each observation is a searcher in the experiments who was either in the control group or in the treatment group for which competition information was shown.

vacancy age information helps direct searchers to vacancies with less competition. The right panel of Figure 12 displays how removing vacancy age affects applications to vacancies with different levels of competition. The treatment causes the largest falls in applications for vacancies with fewer than 5 prior applicants and it has no effects on vacancies that receive over 200 applications.

If vacancy age already allows searchers to find low competition vacancies, then why do the information treatments have an effect? One reason may be that this information allows seekers to identify older vacancies with little competition. Figure 13 shows the treatment effects of competition information for applications to vacancies with different ages. We find that the treatment increases applications to older vacancies, confirming this conjecture.

7. Effects on application outcomes

Our theory predicts that searchers in the treatment will, on average, apply to vacancies with less competition. However, we do not have unambiguous predictions about the quality of applications in the treatment vs the control. We study these questions empirically by comparing the applications submitted by treated and control users across all three experiments.

Treated applicants experience a lower degree of competition. Column 1 of Table 1 reports the results of a regression of the log of the application order on the treatment. We see that treated applications have an order of submission that is 1.5% lower. This may be due to

Table 1: Application Order and Characteristics

	Log App Order		Log Eventual Apps	Third Party Vac.	Viewed
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.0147***	-0.0021**	-0.0127***	0.0017***	
	(0.0013)	(0.0007)	(0.0012)	(0.0002)	
Log App Order					-0.0777***
					(6.78×10^{-5})
R^2	0.040	0.834	0.047	0.006	0.125
Observations	13,846,468	13,846,468	13,846,468	13,846,468	12,765,466
Experiment fixed effects	✓	✓	✓	✓	✓
Vacancy fixed effects		✓			

Notes: This table contains results for a linear regression of applications outcomes on treatment (competition information), where all applications sent in the experimental sample are observations. 'Order' refers to the order in which the application arrived and 'Eventual' is the cumulative applications ever received by a vacancy. 'Third party' refers to a vacancy syndicated from a third party platform. 'Viewed' refers to whether the application was viewed by the employer.

changes in the types of vacancies applied to or changes in the speed with which applications are sent. Column 2 informs this by reporting results from the same regression but with vacancy fixed effects. Conditional on a vacancy, treated applications are submitted .2% faster. This demonstrates that most of the effect of the treatment on speed is due to applications to different vacancies. We investigate this further in columns 3 and 4, which show the estimates from regressions of the eventual applications received by vacancies and whether vacancies were syndicated from a third party. We see that treated applications are sent to vacancies that finish with fewer applications, suggesting that they are less popular. We also see that treated applications are more likely to be sent to third party applications, suggesting that information about competition is especially important for these vacancies.

Given the fact that treated applications arrive earlier to vacancies with less competition, we expect them to have better outcomes. We can conduct a back of the envelope calculation. Table 1 shows that treated applications arrive 1.5% earlier, and that a 1% increase in application order decreases the likelihood of a view by 7.8% (Column 5). Multiplying these two together will get us the expected increase in view probabilities in the treatment of 1.2%. However, this back of the envelope calculation may not be valid if the treatment also changes the types of applications submitted, which is what we investigate next.

Table 2 displays outcomes across treated and control applications for applications sent to native vacancies, which are the ones for which we can measure outcomes. Column 1 demon-

Table 2: Differences in Application Outcomes

	Viewed (1)	Contact (2)	Interview (3)
Treatment	0.0008*	-0.0003	-2.09×10^{-5}
	(0.0004)	(0.0003)	(9.46×10^{-5})
Mean of Y:	0.455	0.273	0.017
R^2	0.052	0.046	0.001
Observations	12,765,466	12,765,466	12,765,466
Experiment fixed effects	✓	✓	✓

Notes: This table contains results for a linear regression of applications outcomes on the treatment in experiment 3. 'Viewed' is an indicator whether the employer viewed the application, 'Contact' is an indicator for whether an employer sent an applicant a message, and 'Interview' is an indicator for whether an employer marked that an interview was conducted.

strates that treated applications to native vacancies are more likely to be viewed by the employers. However, columns 2 and 3 show null effects on the rates at which employers contact or interview applications. A power calculation shows that we do not have the power to detect an effect of the same size as for views for contacts and interviews. This lack of power even with a large sample mirrors similar results in the advertising literature (e.g. Lewis and Rao (2015)).[14] Nonetheless, we do have the power to exclude negative effects on the order of more than .34% for contacts.[15] We also find suggestive evidence that the treatment causes selection into applications, although this effect is non-monotonic in application order (Table B.3)

To summarize, we find that treated applications face less competition, and that this is a function of both applying to different vacancies and to applying to applying earlier. We find that treated applications are more likely to be viewed by native employers, but are underpowered to detect similarly sized effects on other application outcomes. We are able to exclude negative effects of the treatment on application outcomes on the order of .34% or more.

8. Conclusion

Job seekers often lack information about the competition they face for a particular vacancy and their likelihood of getting hired. As a result, they may direct their search in ways that would have been, from their perspective, sub-optimal had they known more information. If signals of job desirability are correlated across searchers, there may be an inefficient imbalance

[15] A simple calculation using the standard error yields $1.96 * .0008/.455 = 00345$.

in applications across vacancies. Digital platforms are in the position to correct this imbalance with the right intervention.

We use data from JOF to study the flow of applications across vacancies and how it is affected by information about the degree of competition for a vacancy. We first show that the degree of competition for a position, as measured by the number of prior applications, affects the likelihood that an employer views, responds to, and interviews a candidate. This suggests that job seekers should value being one of the first to apply to a job. We also show that there is an imbalance in both applications and exposures across vacancies in the same commuting zone. This means that there is a possibility that some job-seekers can direct their job-search to less competitive vacancies and improve market efficiency by doing so. We propose a simple model that rationalizes the above facts and has predictions for the role of information in this type of market.

We test our model by conducting three experiments over the course of five months in 2019. Treated users were shown a simple measure of competition, the number of prior applicants, and this information caused them to redirect their job search. The treatments increased applications to vacancies with little competition and reduced applications to vacancies with a lot of competition. Although our treatments varied the frequency and color with which information was shown, these variations did not have first order implications for our aggregate effects.

While re-balancing applications towards less competitive vacancies is likely efficient, applications induced by the information may be worse. We can exclude large differences in the rates at which applications were responded to or interviewed between the treatment and control group. This suggests that marginal applicants were not substantially worse than applicants in the control group.

Even in the absence of competition information, applicants were able to direct their search towards less competitive vacancies. We use an experiment to show that this is due to the fact that vacancy age is displayed on the platform and is highly correlated with the number of prior applications. When vacancy age was removed, applications to less competitive vacancies dropped. As a corollary, when we added information about prior applicants, applications increased precisely to older vacancies with few prior applications.

We studied just a few of the many information design decisions by the platform. For example, the platform could add or remove information or change where and how information is displayed. The platform could also create better signals of competition and match quality and display these signals to job seekers. Information design decisions may also interact in important ways with other platform design decisions such as ranking and user acquisition strategies.

The welfare implications of information design decisions are difficult to study with user level experiments. A key reason for this difficulty is that actions by seekers and employers exert externalities on each other, meaning that treatment effects from a user level experiment may not be indicative of market outcomes were everyone to be treated. Another difficulty is that the platform has very noisy information about hiring and the quality of those hires. This means there is no direct measure of welfare, either for the searcher or for the employer. Lastly, the level of competition per application is an equilibrium object and the treatment may affect this equilibrium in a manner which our experiment is poorly suited to studying. Future work may be able to address these limitations with commuting zone level experiments, better measurement, and structural models of job search in digital platforms.

Finally, no single platform has a bird's eye view of the entire labor market. Both searchers and employers multi-home across a variety of platforms. As a result, measures of competition on one platform may not fully reflect the true level of competition and optimizations made on one platform might not improve outcomes in the entire labor market. The implications of this fragmentation in labor market platforms are important to understand for market designers and policymakers.

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A. Description and analysis by each treatment arm.

In this section, we describe and analyze the treatment arms of each of the three experiments. We begin with by describing the set of treatments tried across all three experiments. Figure A.1 shows the set of treatment parameters and the experiments which contained an arm with those parameters.

The first dimension along which treatments differed was in whether every vacancy tile was eligible to show competition information. Column 1 contains the set of arms where information could be shown on every tile, while columns 2 and 3 contain arms where information could be shown either every 3 tiles or every 10 tiles (beginning with the first tile on the screen). Next, row 1 displays the set of treatments where information about competition was shown only for vacancies that had fewer than 5 prior applications. For these vacancies, the text 'Be one of the first to apply' was displayed.[16] Row 2 displays the set of treatment arms for which competition information could also be shown for vacancies with more than 4 applications. For these vacancies, the following text could be shown, where appropriate: 'Be one of the first to apply', '5 - 20 applications', '21 - 50 applications', '50 - 200 applications', '201+ applications'. Finally, treatment arms differed by whether they displayed this information in blue (vs grey) always ('All'), just for vacancies with < 5 applications ('First'), or never ('None'). Finally, the grid excludes one treatment arm from Experiment 3, in which some signals were eligible to be shown every tile, while those relating to vacancies with < 5 vacancies could only be shown on every third tile.

Experiment 1 also contained three treatment arms that varied whether the vacancy age was displayed. One of these arms was discussed in section 6. Two other arms removed vacancy age, but added competition signals (either just 'Be the first to apply' or all congestion signals).

To check that the randomization was properly conducted, we preformed a set of balance tests. Figure A.2 displays these tests, where the p-value for the difference in means on pre-treatment covariates is displayed for every treatment arm in each experiment. Across four covariates (Age, Android User, Gender, and US user), we find differences that are not statistically significant at a 5% p-value. This evidence suggests a proper randomization of the treatment arms by Facebook.

[16] The text was also translated into the appropriate language for each locale.

Figure A.1: Treatment Arms for Experiments

	Every Tile	Every 3 Tiles	Every 10 Tiles
Only "Be one of the first to apply"	Exp. / Blue 1 / None	Exp. / Blue 2 / All 3 / All	Exp. / Blue 2 / All
All Congestion Signals*	Exp. / Blue 1 / None 3 / First	Exp. / Blue 2 / All 2 / None 2 / First 3 / First	Exp. / Blue 2 / All 2 / None 2 / First

*Experiment 3 also had a treatment arm that displayed `Be one of the first to apply' on only the 3rd tile when eligible but displayed other congestion information in grey on every tile when eligible.

Notes: This figure displays the experiments during which each combination of treatments appeared. Information was presented either every tile, every 3 tiles (starting with tile 1), or every 10 tiles (starting with tile 10). Treatment arms varied by whether only under-subscribed vacancies (< 5 prior applications) were marked with competition information, or whether all eligible vacancies were marked with congestion information. Lastly, in certain cases competition information was given a blue color. Values of 'First' in the 'Blue' column denote that only signals for under-subscribed vacancies were given a blue color.

Figure A.2: Covariate balance test p-values across experiments

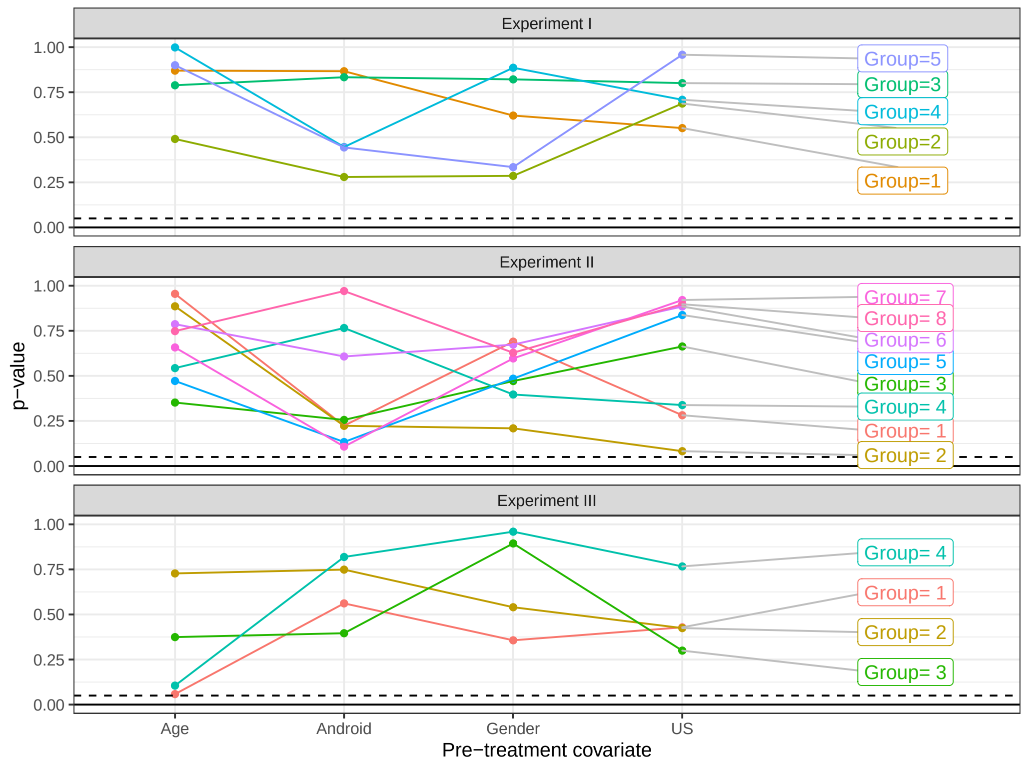
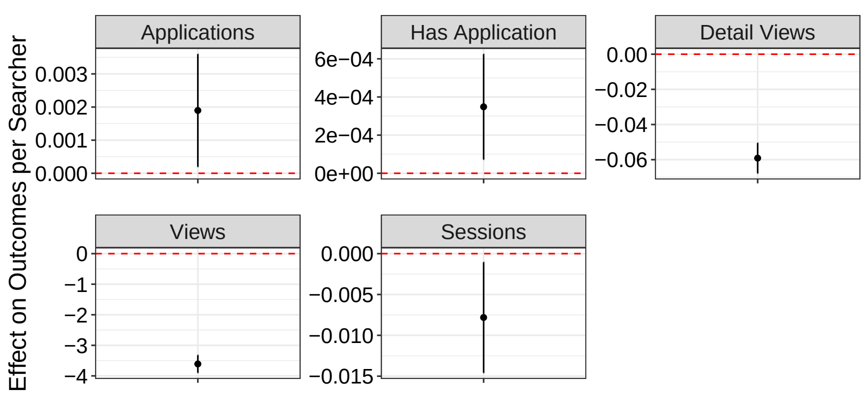
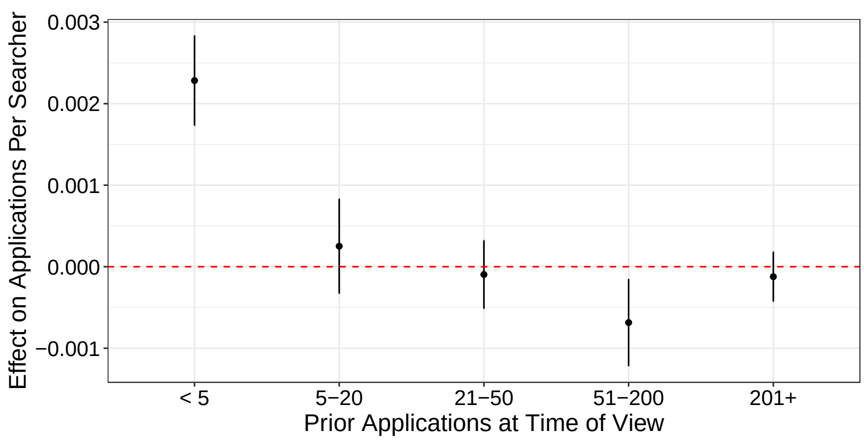


Figure A.3: Effects (in levels) of revealing congestion information on job search behavior and outcomes



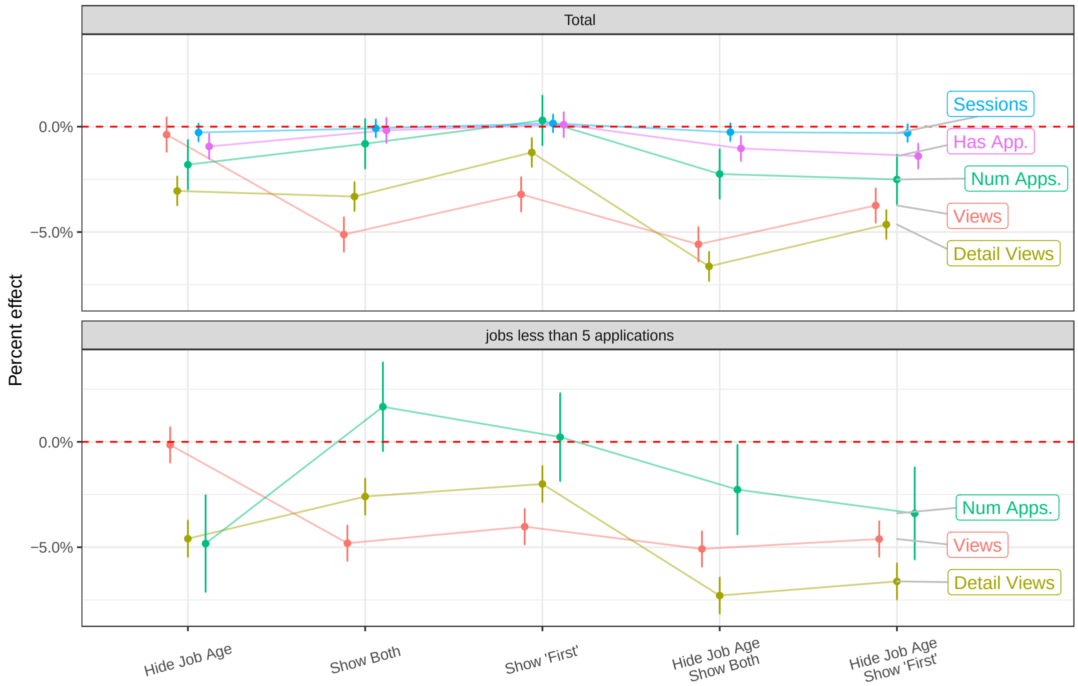
Notes: This figure plots the average effect of the treatment (pooled across all arms) in levels. Each observation is a searcher in an experiment and all treatments that included information about prior applications were pooled.

Figure A.4: Effects (in levels) of congestion information on applications to different status vacancies



Notes: This figure plots the average effect of the treatment (pooled across all arms) in levels. Each observation is a searcher in an experiment and all treatments that included information about prior applications were pooled.

Figure A.5: Treatment Effects for Experiment 1



A.1 Effects by Treatment Arm

Next, we discuss the by-arm treatment effects for each treatment and experiment. We begin with Experiment (Figure A.5). Columns 1, 4, and 5 of of the figure plot the treatment effects where the vacancy age is hidden. Columns 2 - 5 plot treatments where competition information is added. Broadly, the treatments where vacancy age is hidden experience drops in views, detail views and applications. Columns 2 and 3, where competition information is added but vacancy age remains. The two treatments have similar effects on our outcomes.

Figure A.6 displays the effects of the separate treatment arms of experiment 2. Broadly, the effects are of similar magnitude across arms. The clearest difference is that there is a bigger drop in views when competition information is displayed every 3 tiles rather than every 10 tiles. This is expected since the competition information takes up an additional line of text and therefore fewer vacancies can be shown in the 'every 3' treatments.

Finally, Figure A.7 displays the effects of the separate treatment arms of experiment 3. As in the other experiments, the effects on applications and sessions are similar across treatment arms. As before, the more frequently competition information is shown, the fewer vacancies

Figure A.6: Treatment Effects for Experiment 2

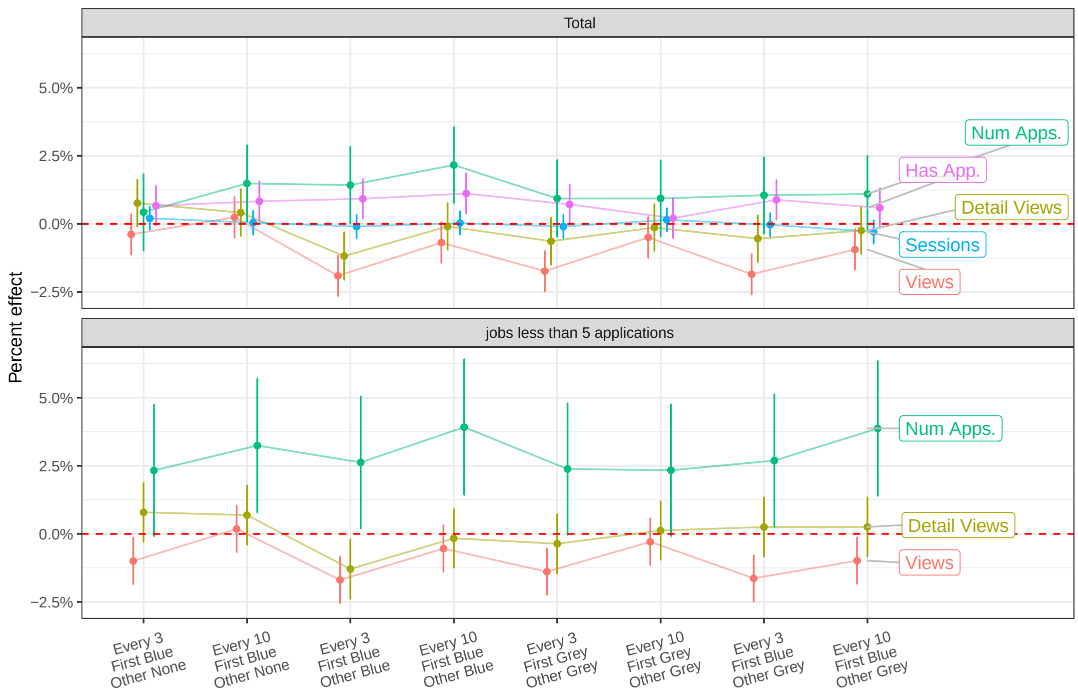


Figure A.7: Treatment Effects for Experiment 3

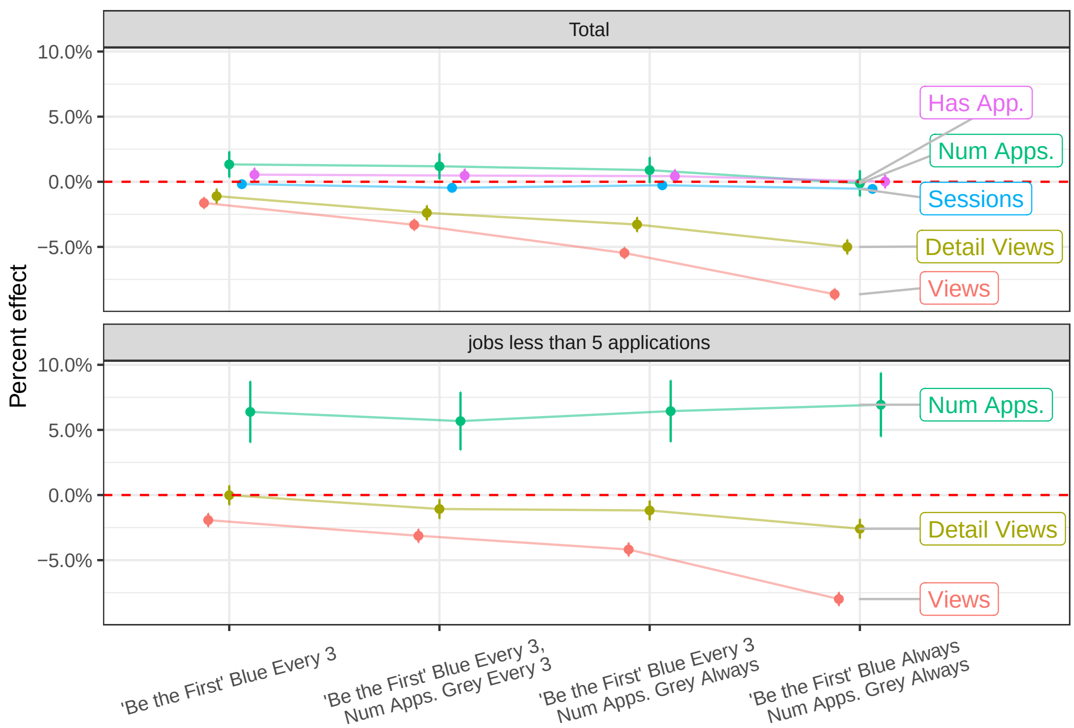


Table A.1: Treatment effects pooled across all three experiments

	Num. App. (1)	Has App. (2)	Detail Views (3)	Views (4)	Sessions (5)
Treatment	0.0019*	0.0003*	-0.0591***	-3.609***	-0.0078*
	(0.0009)	(0.0001)	(0.0044)	(0.1463)	(0.0034)
Mean of Y:	0.332	0.105	2.727	92.455	4.162
R^2	0.002	0.007	0.002	0.001	0.008
Observations	29,375,533	29,375,533	29,375,533	29,375,533	29,375,533
Experiment fixed effects	✓	✓	✓	✓	✓

Notes: Effects of the competition sginal treatment pooled across experiment.

are seen by the searchers.

Table A.2: Treatment effects pooled across all three experiments - by application type

	0 - 4 App.	5 - 20 App.	21 - 50 App.	51 - 200 App.	201+ App.
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0023***	0.0003	-9.58×10^{-5}	-0.0007*	-0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Mean of Y:	0.332	0.105	2.727	92.455	4.162
R^2	0.001	0.001	0.002	0.002	0.010
Observations	29,375,533	29,375,533	29,375,533	29,375,533	29,375,533
Experiment fixed effects	✓	✓	✓	✓	✓

Notes: Effects of the competition sginal treatment pooled across experiment.

B. Why does the effect size vary across experiments?

We now investigate why the effects of competition information on applications vary so greatly across the three experiments. We show that the details of the treatment implementation, changes in the demographics of users, and changes in market tightness do not explain the differences in treatment effects.

B.1 Differences in treatment

As explained in Appendix A, each of our three experiments had several treatment variations. One concern is that our main results are driven by differences in the exact implementation of the treatment across experiments. In this section, we compare two *identical* treatment arms across experiments 2 and 3 and show that the differences in experimental treatment effects persist even for identical treatments.

The first repeated treatment is one in which the 'Be one of the first to apply' signal is eligible to be shown in blue every three tiles. The estimates and 95% confidence intervals for this treatment are shown in Comparison A of Figure B.1. The effect of the treatment on applications to under-subscribed vacancies is more than twice as large in experiment 3 than it is in experiment 2 (pval: 0.016). There are also substantial differences in other outcomes, such as the number of detail views and views for all vacancies.

Similarly, there are differences in the effects of the other repeated treatment between experiment 2 and 3. This treatment displayed competition information every 3rd tile for all types of information. Furthermore, 'Be one of the first to apply' is shown in blue. The effect of the treatment on applications to under-subscribed vacancies is more than twice as large in experiment 3 than it is in experiment 2 (pval: 0.07). There are also substantial differences in other outcomes, such as the number of detail views and views for all vacancies. As a result, we conclude that the differences in experiments are not driven by the specific implementation of the competition signal.

B.2 Differences in observable user characteristics and market conditions.

Another reason for the differences in treatment effects across experiments may be that the user composition or market conditions are changing. JOF is a fast growing and global platform, so it is conceivable that these factors could change over a period as short as a month.

Table B.1 reports summary statistics for user characteristics for the three experiments.

Figure B.1: Effects of the same treatment across experiments

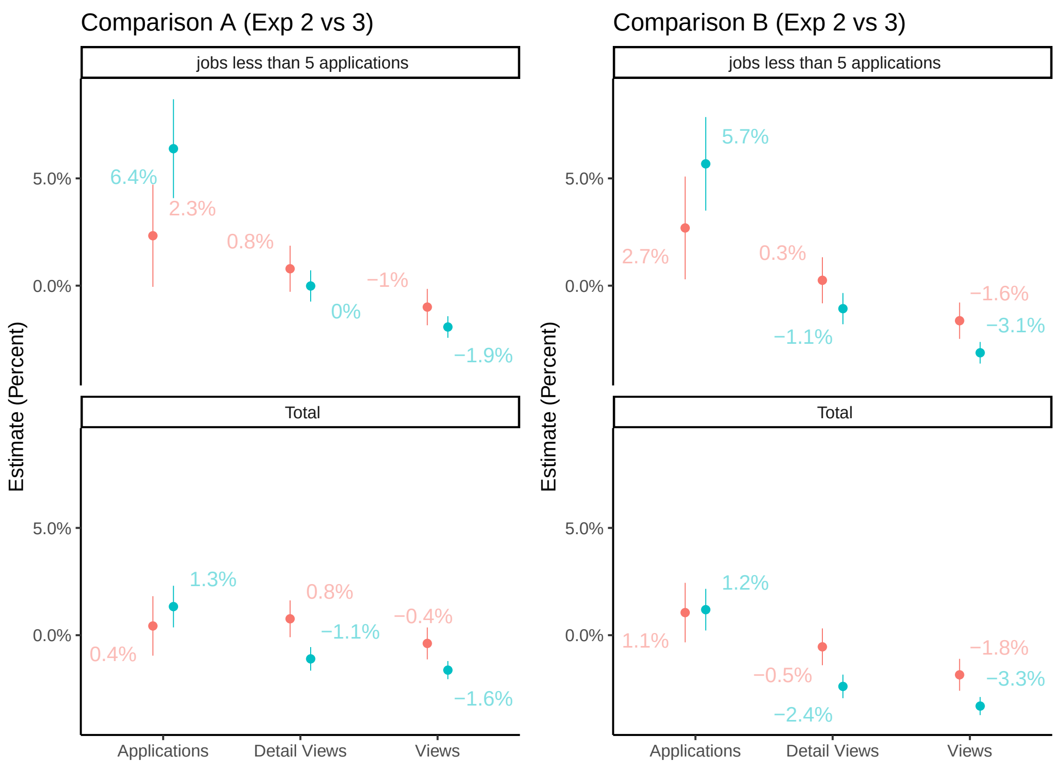
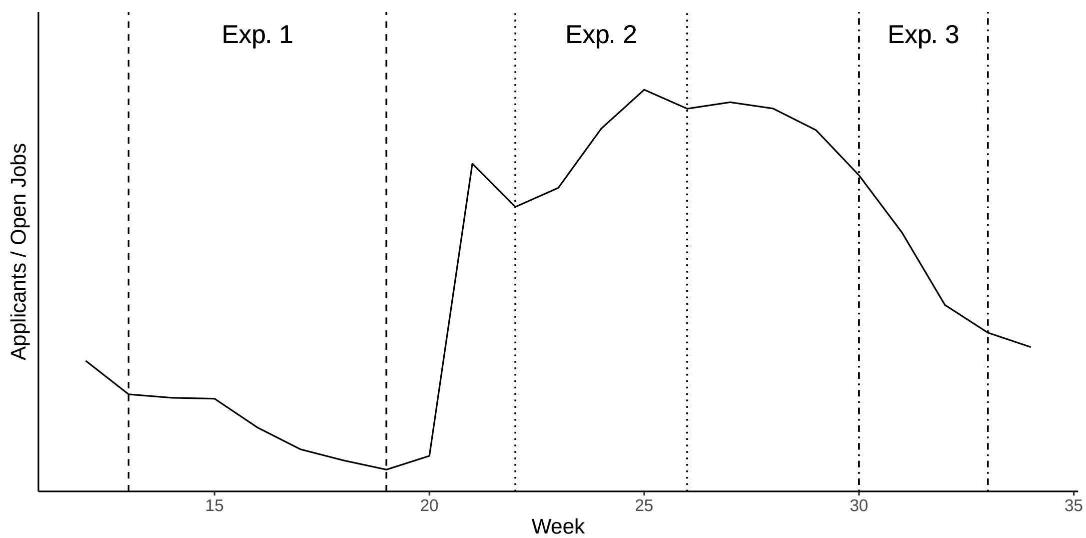


Figure B.2: Evolution of market tightness over time



There are some compositional differences across the experiments—for example, by Experiment III, the fraction of users who are from the US has declined, as has the fraction that are female. Furthermore, Experiment III has a lower share of users who had used the Jobs product in the two weeks prior to the experiment than Experiment II. We can also measure the market tightness of each commuting zone in our sample - defined by the prior week's number of applications divided by number of vacancies. Figure B.2 plots the evolution of this quantity over time and by region. We see that tightness increases after Experiment I and falls after Experiment II.

Next, we test for heterogeneous effects based on these factors, and find that they are not large enough to explain the differences between experiments. We estimate separate regressions interacting a dichotomized version of each variable with the treatment, where the outcome variable is applications to under-subscribed jobs. The results of these regressions are reported in Figure B.3. We see that there is some heterogeneity in treatment effects for those who've used the product before and for US users. However, this heterogeneity is not precisely estimated.

B.3 Differences in viewed vacancies across experiments

We now consider whether differences in the vacancies shown to job seekers can explain the differential effects of the experiments. As in the proceeding section, we first measure whether

Table B.1: Control group demographics over the three experiments

	25th	Median	75th	Mean	StDEv	exp
Exp I (n = 1,763,735)						
Age	26	33	44	35.95	13.63	1
US User	NA	NA	NA	0.25	NA	1
Friends	219	444	873	746.74	896.28	1
Used Jobs Pre Exp.	NA	NA	NA	0.27	NA	1
iOS User	NA	NA	NA	0.34	NA	1
Male	NA	NA	NA	0.59	NA	1
Exp II (n = 863,215)						
Age	25	32	42	34.45	13.18	2
US User	NA	NA	NA	0.21	NA	2
Friends	203	437	922	785.59	969.06	2
Used Jobs Pre Exp.	NA	NA	NA	0.38	NA	2
iOS User	NA	NA	NA	0.27	NA	2
Male	NA	NA	NA	0.54	NA	2
Exp III (n = 3,265,172)						
Age	24	31	42	34.23	13.74	3
US User	NA	NA	NA	0.20	NA	3
Friends	173	399	873	747.61	962.37	3
Used Jobs Pre Exp.	NA	NA	NA	0.32	NA	3
iOS User	NA	NA	NA	0.31	NA	3
Male	NA	NA	NA	0.51	NA	3

Notes: User characteristics by experiment. 'Used Jobs Pre Exp.' is an indicator for whether the user used the job board in the two weeks prior to the experiment.

Figure B.3: Heterogeneous Treatment Effects - Applications to Under-subscribed Vacancies

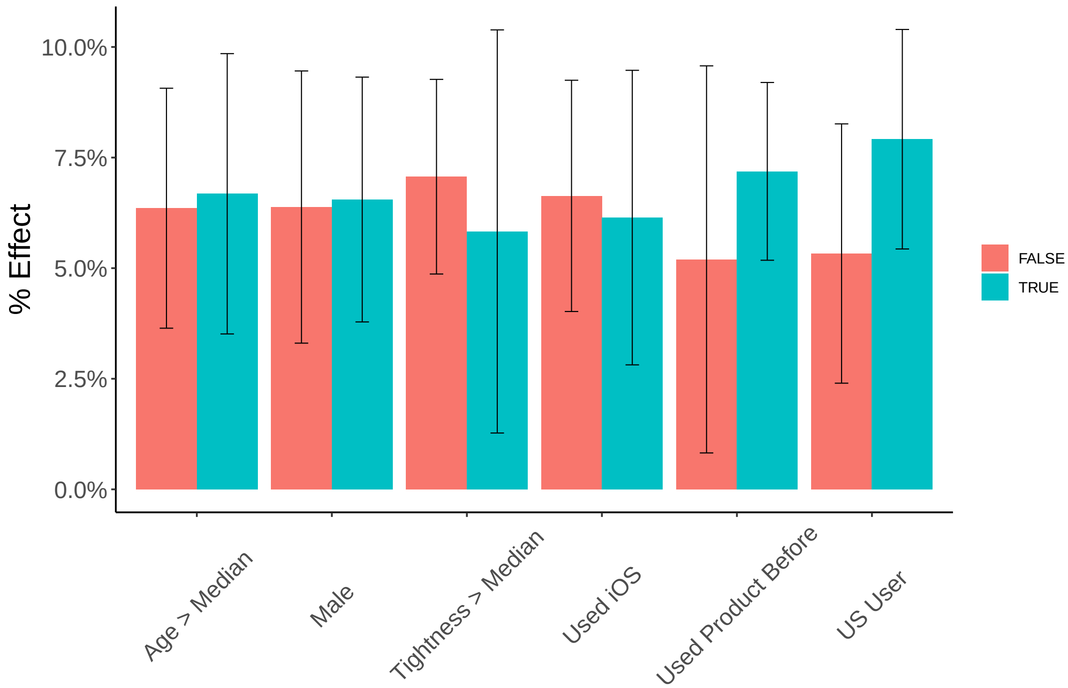
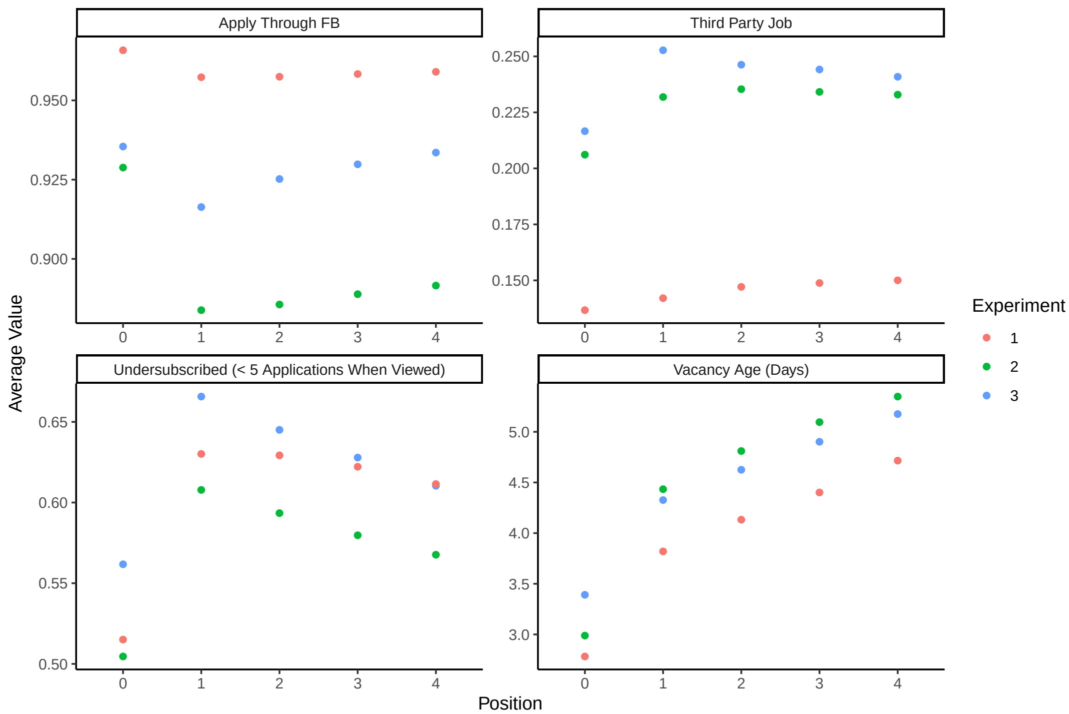


Table B.3: Differences Conditional on Application Order

	Viewed	Contact	Interview
Treatment	0.001	0.002*	0.000
	(0.001)	(0.001)	(0.000)
Log(Order)	-0.018***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)
Treat * Log(Order)	0.000	-0.001**	0.000
	(0.000)	(0.000)	(0.000)
N	5472586	5472586	5472586
Vacancy FE	X	X	X

Notes: This table contains results for a linear regression of applications outcomes on the treatment in experiment 3. 'Viewed' is an indicator whether the employer viewed the application, 'Contact' is an indicator for whether an employer sent an applicant a message, and 'Interview' is an indicator for whether an employer marked that an interview was conducted.

Figure B.4: Characteristics of Vacancies Viewed Across Experiments



there is any shift in vacancy characteristics over time. We then test whether there are heterogeneous treatment effects as a result of these characteristics.

Figure B.4 displays the average values of our measured variables across the three experiments (colors) and display position in the interface (x-axis). Our first measure of job characteristics is whether the candidate can apply to the job through Facebook. We see that for all experiments, the share of exposures to these jobs is above 85%, although there are some differences. Our second measure is whether the job was created through Facebook's portal (native) or whether it was syndicated from a third-party. We see that most vacancies are native and that there are fewer third-party vacancies in experiment 1. Our next two-measures incorporate information that occurs on the platform. Namely, we can observe the prior number of applications and vacancy age at the time of viewing. We see some differences, but these are not monotonic in experiment launch date. In particular, Experiment II is less likely to have under-subscribed vacancies be viewed, while Experiment I has a lower vacancy age exposed.

Next, we consider whether these characteristics can explain treatment effect heterogeneity in Experiment III. Table B.4 displays regressions where the outcome is whether the user applied to the first vacancy viewed in the experiment. We exclude vacancies shown in positions below the first because the depth of search is an endogenous outcome and we exclude vacancies that could not be applied to through Facebook.[17]

The explanatory variables are vacancy and vacancy by user characteristics. Column (1) displays the results while including the variables considered in Figure B.4. We see that these variables do not explain treatment effect heterogeneity. Column (2) further adds the characteristics of the vacancy poster - in particular whether the poster had a 'local' page on Facebook and whether they had a 'business' page on Facebook. It also adds an indicator for whether the vacancy and the searcher are located in the same city. The interactions are not statistically significant for any of these variables.

Finally, in column (3), we add the algorithmic score which predicts whether a given searcher will apply to a particular job. This score is generated using a proprietary machine learning algorithm and does substantially predict treatment effect heterogeneity. Furthermore, this effect is an order of magnitude larger than the average treatment effect. This heterogeneity demonstrates that there is scope for the match between searcher and vacancy to change over time and to cause treatment effect heterogeneity.

[17] This designation sometimes changed over time and a negligible fraction of these jobs did have an application.

Table B.4: Characteristics of Vacancies Viewed Across Experiments

	Has Application		
	(1)	(2)	(3)
Treatment	0.0004***	-0.0002	-0.0006
	(1e-04)	(4e-04)	(0.0004)
Treatment * Third Party	0.0000	0.0001	0.0001
	(1e-04)	(1e-04)	(0.0001)
Treatment * Age > 5 Days	0.0000	0.0000	0.0002
	(1e-04)	(1e-04)	(0.0001)
Treatment * Same City		0.0001	0.0001
		(1e-04)	(0.0001)
Treatment * FB Local		0.0000	0.0001
		(1e-04)	(0.0001)
Treatment * FB Business		0.0005	0.0006*
		(4e-04)	(0.0004)
Treatment * Algorithmic Match Score			0.0053***
			(0.0012)
Num.Obs.	9020389	9020389	9020389
R2	0.000	0.000	0.004
R2 Adj.	0.000	0.000	0.004

Notes: Regression of whether the user applied to the first vacancy shown as a function of the treatment and interactions. Non-interacted covariates are not shown. Observations for which the first job shown could not be applied to through Facebook were excluded.

Table B.5: Tradeoffs

	Application			
	(1)	(2)	(3)	(4)
Age Shown × Vacancy Age = 11-20	-0.0250			
	(0.0454)			
Age Shown × Vacancy Age = 6-10	0.0277			
	(0.0447)			
Age Shown × Vacancy Age = new	0.0897*			
	(0.0361)			
Prior Apps Shown × Prior Apps = 0 - 4		0.0331$^{\cdot}$	-0.1292**	-0.1543*
		(0.0171)	(0.0459)	(0.0662)
Prior Apps Shown × Prior Apps = 200+		-0.0231	-0.0229	-0.0116
		(0.0184)	(0.0184)	(0.0260)
Prior Apps Shown × Prior Apps = 21 - 50		-0.0370$^{\cdot}$	-0.0369$^{\cdot}$	-0.0207
		(0.0216)	(0.0216)	(0.0304)
Prior Apps Shown × Prior Apps = 51 - 200		-0.0264	-0.0264	-0.0399
		(0.0195)	(0.0195)	(0.0275)
Prior Apps Shown × Prior Apps = 5 - 20		0.0044	0.0045	0.0048
		(0.0205)	(0.0205)	(0.0289)
< 5 Apps × Prior Apps Shown × New			0.1686***	0.1826**
			(0.0441)	(0.0639)
Mean of Y:	0.017	0.017	0.017	0.017
Sample:	All	All	All	Has Age
Observations	9,578,784	9,578,784	9,578,719	4,789,293
Vacancy Age fixed effects	✓	✓	✓	✓
Prior Apps fixed effects	✓	✓	✓	✓
Treatment Group fixed effects	✓	✓	✓	✓

Notes: .

Table B.6: Tradeoffs OLS Exp 2

	Application	
	(1)	(2)
Treatment × Prior Apps = 0 - 4	0.0004***	0.0071***
	(0.0001)	(0.0003)
Treatment × Prior Apps = 5 - 20	0.0002	0.0009*
	(0.0004)	(0.0005)
Treatment × Prior Apps = 21 - 50	-0.0002	-0.0045***
	(0.0006)	(0.0006)
Treatment × Prior Apps = 51 - 200	9.99×10^{-5}	-0.0082***
	(0.0006)	(0.0006)
Treatment × Prior Apps = 200+	0.0009	-0.0045*
	(0.0020)	(0.0023)
Treatment * New × Prior Apps = 0 - 4		-0.0074***
		(0.0003)
Treatment * New × Prior Apps = 5 - 20		-0.0009*
		(0.0004)
Treatment * New × Prior Apps = 21 - 50		0.0054***
		(0.0005)
Treatment * New × Prior Apps = 51 - 200		0.0104***
		(0.0005)
Treatment * New × Prior Apps = 200+		0.0066***
		(0.0016)
Mean of Y:	0.01	0.01
R^2	0.010	0.010
Observations	7,117,909	7,117,759
Vacancy Age fixed effects	✓	✓
Prior Apps fixed effects	✓	✓

Notes: .