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# Cheap search, picky workers? Evidence from a field experiment

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## Abstract

Search frictions impede the labor market. Despite this indisputable fact, it is a priori unclear how job search costs affect search duration and unemployment: lower search costs make it easier to find a job, reducing search duration and unemployment, but may also increase the reservation wage, increasing search duration and unemployment. I collaborate with a recruiting company to directly test the effects of lower search costs in a field experiment among approximately 400 IT professionals in Switzerland. I find that workers are more likely to search for detailed job information, but not to file a job application, when search costs are lower. These findings are consistent with an increase in the reservation wage. Lower search costs might lead to picky workers, but fail to ultimately reduce search duration and unemployment.

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# 1 Introduction

The importance of information in job search has long been central to economists' understanding of the labor market (Stigler, 1962). Search theory predicts that lower search costs lead to lower search duration and unemployment (Mortensen and Pissarides, 1994). The McCall (1970) model, in contrast, predicts that lower search costs increase the reservation wage, thereby increasing search duration and, ultimately, unemployment. Do workers get pickier when search costs decrease? I address this question in a field experiment which experimentally varies search costs on the labor market.

This study is, to the best of my knowledge, the first attempt to experimentally vary the costs of access to job information. Recent research shows that relatively minor interventions, e.g. providing information on the number of applicants (Gee, 2019) or removing optional requirements (Abraham and Stein, 2022), can have significant effects on job search behavior. This study also relates to experimental work that evaluates various programs for job search advice and monitoring (Graversen and van Ours, 2008; Crépon et al., 2013; Behaghel et al., 2014; Altmann et al., 2018; Belot et al., 2018). Pertinent observational studies investigate how the internet changed job search (Kuhn and Skuterud, 2004; Kuhn and Mansour, 2014; Kroft and Pope, 2014).

I collaborate with a recruiting agency in Zurich to assess the effects of search costs in a natural field experiment. In this setting, recruiters identify suitable workers and send them concise messages to promote the vacancy. I experimentally vary the cost of accessing more detailed job information. While workers in both the treatment and control group can access information about job characteristics by contacting the recruiter, only workers in the treated group are provided with websites that directly show the candidate detailed information about job characteristics. Thus, treated workers' search costs are lower because they need only click on the website hyperlink to view the additional information.

Results show that the decrease in search costs increases the number of workers who search for detailed job information from 20.1% to 37.7% ($p < 0.01$). Consistent with increased reservation wages in the McCall (1970) model, I find no increase in job applications. If anything, workers in the treatment group are less likely to file a job application (1.9% vs. 4.2%, $p = 0.18$).

# 2 Experimental design

The field experiment is run in collaboration with a recruiting agency. The recruiting agency is located in Zurich and has a geographical focus on the German speaking part of Switzerland. Two agents recruit professionals for various roles in IT. Typical vacancies (e.g. software engineers, project managers, or network administrators) require specific skills and education.

Recruiters in this setting actively approach workers to fill a given vacancy. The recruiter screens online platforms (e.g. LinkedIn) for workers with the required skill set. The identification of workers (which is identical in the control and treatment condition) relies on the experience of the recruiter, who usually infers a worker's skill set and willingness to consider a new job from the limited information available on online platforms. Once a suitable worker is identified, the recruiter sends her an unsolicited offer message. This offer message reveals only basic job facts like the job title and the approximate office location. The worker can respond to the offer message to obtain more detailed job information from the recruiter. The treatment condition (described below) simplifies access to detailed job information. Eventually, the worker decides whether or not to file a job application. The recruiting agency receives its agency fee when worker and employer agree on a contract.

The experiment varies the ease of access to detailed job information. The recruiting agency uses a software, that was specifically developed for this field experiment, to automatically create randomized offer messages for workers. The software randomly allocates offer messages to the two experimental conditions, with a 50% probability for the control and treatment condition. The resulting offer message is either a short message (control group), or an otherwise identical message augmented with a web link (treatment group).[1] The web link in the treatment group leads to a website where the worker sees information about working hours, work environment, location, salary, and the recruiter.[2] The control group does not have access to the website, but both the treatment and control group can contact the recruiter to obtain the information on the website. Search costs are lower in the treatment condition if obtaining information through a message or phone call to the recruiter is more costly than a look at the website. Workers are unaware of the intervention's experimental nature.

## 3 Data

All interactions with workers are recorded by the recruiters. These include when a worker reacts to an offer message (possibly by LinkedIn, Email, or phone), when recruiter and worker discuss the vacancy at a phone call, and when an application is filed. These interactions are recorded for all workers, in both the treatment and control group. In addition, all activities on the websites are recorded, including access of the website and clicks on expansion panels. Website activities are available for workers in the treatment group only, as they are the only ones provided with a website link.

I use two main binary outcome variables: search and applications. A worker engages in search if she reacts to the offer message in any way. This definition includes opening of the website and contact with the recruiter e.g. via messages on LinkedIn, email, and phone calls. Applications are clearly defined events which involve the candidate submitting application materials, recorded by the recruiters.

Most workers have a public profile on LinkedIn. Information from there is available for all workers whose profile could be unambiguously identified. These data include the number of connections on LinkedIn, number of reported jobs and employers, reported work experience overall and at the current job, number of reported skills and the number of endorsements for these skills, and reported degrees.

Table I shows summary statistics for the study sample. Two recruiters sent out 421 randomized offer messages between July 17, 2018 and August 15, 2018. 207 offers (49.2%) were randomly assigned to the treatment group, the remaining 214 offers were assigned to the control group. Among all 421 contacted workers, 28.7% searched for detailed job information and 3.1% eventually filed an application. As expected for the IT sector in Switzerland, the sample is predominantly male, with a female share of 4.3%. 80.5% of workers were not sourced on LinkedIn (i.e. the recruiter found them somewhere else), but the LinkedIn profile could be unambiguously identified for 62.7% of the sample. Among the 264 workers with available LinkedIn data, the average worker is connected to 166

[1]Stylized messages in the control and treatment group are depicted in Appendix A. All appendices are included at the end of the paper.

[2]A detailed description and illustration of the website is provided in Appendix B.

other LinkedIn users. The average worker reports 4.7 different jobs at 0.79 employers, 12.4 years of experience across jobs and 2.8 years at the current job. LinkedIn users can report skills (e.g. "Stata", "Java", "Project management") and endorse each other for these skills. In my sample, the average worker received 50 endorsements for 22 skills. 17% report a Bachelor's degree and 20% report a Master's degree.

**Table I** – Summary statistics

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| Treatment | 0.492 | 0.501 | 0 | 1 | 421 |
| Search | 0.287 | 0.453 | 0 | 1 | 421 |
| Application | 0.031 | 0.173 | 0 | 1 | 421 |
| Female | 0.043 | 0.203 | 0 | 1 | 421 |
| Not sourced on LinkedIn | 0.805 | 0.396 | 0 | 1 | 421 |
| LinkedIn data available | 0.627 | 0.484 | 0 | 1 | 421 |
| LinkedIn connections | 166.136 | 142.987 | 0 | 500 | 264 |
| Number of reported jobs | 4.705 | 2.746 | 0 | 16 | 264 |
| N. of reported employers | 0.788 | 1.177 | 0 | 6 | 264 |
| Reported work experience [y] | 12.375 | 6.897 | 0 | 49 | 264 |
| Reported tenure [y] | 2.760 | 2.871 | 0 | 19 | 264 |
| N. of reported skills | 22.106 | 14.472 | 0 | 50 | 264 |
| N. of skill endorsements | 50.428 | 90.890 | 0 | 748 | 264 |
| Reported Bachelor's degree | 0.167 | 0.373 | 0 | 1 | 264 |
| Reported Master's degree | 0.201 | 0.401 | 0 | 1 | 264 |

Notes: The table provides summary statistics for the 421 workers in the field experiment (first six variables) and the subset of 264 workers who could be identified on LinkedIn (other variables). The columns depict means, standard deviations, minimum values, maximum values, and the number of workers.

Table II in Appendix C depicts worker characteristics for the control and treatment group separately. Only one out of 13 variables (the number of reported skills) is significantly different across groups, suggesting that the randomization procedure achieved balance on observable characteristics.

## 4 Results

Workers in the treatment group are more likely to search for detailed job information. 20.1% of workers in the control group obtain detailed job information through the recruiter, 95% confidence interval [14.6%, 25.5%]. 37.7% of workers in the treatment group obtain detailed job information, confidence interval [31.1%, 44.3%]. The website increases the share of workers who obtain detailed job information by 17.6 percentage points ($= 37.7\% - 20.1\%, p < 0.01$, two-sample z-test of proportions). This result indicates that the experimental intervention meaningfully decreases search costs, thus promoting search.

The increase in search does not translate into more applications. If anything, the opposite is true: 1.9% in the treatment group file an application, confidence interval [0.1%, 3.8%], as compared to 4.2% in the control group, confidence interval [1.5%, 6.9%]. The difference is not statistically significant on conventional levels ($p = 0.18$, two-sample z-test of proportions).[3] The finding that applications do not increase in the treatment group suggests that workers become pickier as search costs decrease.

The lower application rate in the treatment group cannot be explained by less personal contact with recruiters. A substantial share of workers in the treatment group (15.5%) gets in contact with recruiters. The difference to the control group is not statistically significant and, when taken at face value, has modest impact on the interpretation of the results on applications. In particular, the 4.6 percentage points difference in personal interactions can explain a 1.0 percentage point lower application rate in the treatment group if, as in the control group, 21% of personal interactions translate into job applications.

## 5 Conclusions

This study is an attempt to experimentally study the effects of a decrease in job search costs. I find that lower search costs lead to more search, but not to an increase in job applications. These findings are consistent with the McCall (1970) model, which predicts that lower search costs increase workers' reservations wages. Intuitively, cheap search means that continued search is relatively attractive and workers decide to wait for an exceedingly attractive job offer—in terms of wage or other workplace amenities.

While the results of this study are consistent with workers getting pickier in response to lower search costs, other economic and psychological mechanisms may apply. For instance, workers may be subject to a sunk cost fallacy or interpret a costly search act as a signal of their interest in the job. Distinguishing increased reservation wages from alternative explanations remains an interesting open question for future research.

Whether pickier workers ultimately end up with better jobs is an important follow-up question that could be investigated in a similar setting. The current study lacks power to investigate effects on job duration or other measures of match quality, but a large-scale replication may well answer this question.

Future research may also investigate whether the results reported in this paper generalize to other industries, countries, and labor market conditions. Are picky workers relevant on aggregate? Could this phenomenon contribute to an outward shift of the Beveridge curve? Answers to these questions may have substantial implications for our understanding of labor markets.

[3] The experiment has limited statistical power at the application stage. The sample size of 421 allows to detect an increase in the search rate from 20.1% to 32.1%, and an increase in the application rate from 4.2% to 11.6%, at the 5% significance level with 80% power.

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# Appendix

## A Stylized recruiter messages

### Control group

*Dear John Doe,*
*I am charged with the search for a Senior System Engineer in Zurich. This job involves the maintenance of existing IT systems as well as the introduction of new services and features. I am convinced that this would be an exciting opportunity for you, and I would be happy to answer your questions in a confidential conversation.*
*Kind regards,*
*Ron Recruiter*

### Treatment group

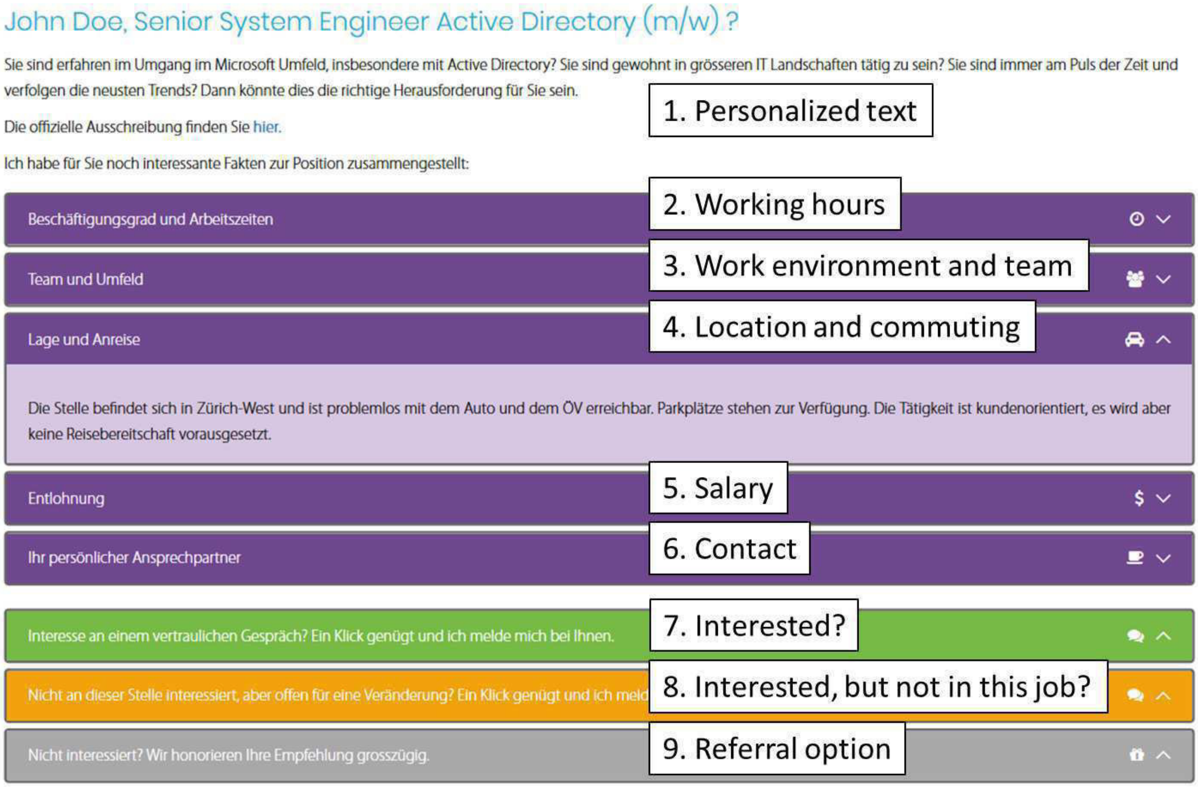
*Dear John Doe,*
*I am charged with the search for a Senior System Engineer in Zurich. This job involves the maintenance of existing IT systems as well as the introduction of new services and features. I am convinced that this would be an exciting opportunity for you, and I would be happy to answer your questions in a confidential conversation.*
*Please find detailed information about the vacancy at the following link:*
*https://www.jobdetails.ch/recruiter/0418us/Doe*
*Kind regards,*
*Ron Recruiter*

# B Website

When a worker in the treatment group clicks on the link in the offer message, the following content appears on the website illustrated in Figure 1:

1. A personalized text drafted by the recruiter
2. Information about working hours
3. Information about work environment and team
4. Information about location and commuting
5. Information about the salary
6. Information about the recruiter
7. A green button to indicate interest in the vacancy
8. An orange button to indicate interest, albeit not in the given vacancy
9. Information about referral rewards

**Figure 1** – Illustration of the website (German, with annotations)




The information content in 2 to 9 is provided in expansion panels. These panels expand upon a mouse click, to display further information (as illustrated in the third expansion panel in Figure 1).

A click on the green or orange expansion panel indicates interest and notifies the recruiter, who will then contact the worker. If desired, the worker may enter the email address or phone number she wants to be contacted at.

# C Additional tables

**Table II** – Randomization check

| | Control | Treatment | Difference | N |
|---|---|---|---|---|
| Female | 0.033 | 0.053 | 0.020 | 421 |
| | (0.178) | (0.225) | (0.301) | |
| Not sourced on LinkedIn | 0.790 | 0.821 | 0.032 | 421 |
| | (0.408) | (0.384) | (0.415) | |
| LinkedIn data available | 0.607 | 0.647 | 0.040 | 421 |
| | (0.489) | (0.479) | (0.399) | |
| LinkedIn connections | 176.185 | 156.388 | -19.797 | 264 |
| | (151.036) | (134.570) | (0.262) | |
| Number of reported jobs | 4.946 | 4.470 | -0.476 | 264 |
| | (2.799) | (2.683) | (0.159) | |
| N. of reported employers | 0.854 | 0.724 | -0.130 | 264 |
| | (1.227) | (1.127) | (0.371) | |
| Reported work experience [y] | 12.585 | 12.170 | -0.415 | 264 |
| | (6.837) | (6.974) | (0.626) | |
| Reported tenure [y] | 2.672 | 2.845 | 0.173 | 264 |
| | (2.861) | (2.888) | (0.625) | |
| N. of reported skills | 24.208 | 20.067 | -4.141** | 264 |
| | (14.247) | (14.449) | (0.020) | |
| N. of skill endorsements | 58.208 | 42.881 | -15.327 | 264 |
| | (100.032) | (80.706) | (0.171) | |
| Reported Bachelor's degree | 0.154 | 0.179 | 0.025 | 264 |
| | (0.362) | (0.385) | (0.584) | |
| Reported Master's degree | 0.208 | 0.194 | -0.014 | 264 |
| | (0.407) | (0.397) | (0.783) | |

Notes: Characteristics of workers in the control (column 1) and treatment (column 2) group. Differences are depicted in column 3. Standard errors (columns 1 and 2) and p-values (column 3) in parenthesis.