Labor Demand and Supply Across Occupational Boundaries

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Abstract: Occupations organize labor, but whether and how much they contribute to matching frictions is not well understood. We use novel job postings data to measure to what extent skill requirements overlap between occupations. We then analyze data on how recruiters and job-seekers contact each other, both within and across occupations. Recruiters and job seekers are less likely to contact each other as overlap between the recruiters target occupation and the job-seeker's previous occupation decreases. Recruiters value previous experience in the target occupation, and job-seekers target jobs where they have work experience. Recruiters who operate in tight markets are more likely to contact job-seekers who have not worked in the target occupation but are more demanding in terms of work experience. These patterns of search across occupations are consistent with actual probabilities of accepting a new occupation.

Keywords: occupations, mobility, job requirement overlap, labor demand, labor supply.
JEL Codes: J24, J62, J63, J64

1 Introduction

Occupations are central to the labor market. Firms typically post their demand for labor by listing the job title or occupation of the vacancy, and job-seekers target their search activities to occupations that they are familiar with. Occupational dictionaries define the set of skills required to perform the job and also the tasks that need to be delivered. Occupations may therefore segment the labor market into sub-markets, introducing labor market frictions, but is not clear to what

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extent sharp boundaries demarcate these sub-markets. Indeed, the boundaries between occupations appear fuzzy as many occupations use similar skills and tasks, which can create overlap between different types of jobs. For example, project management skills are relevant in fields as diverse as construction, IT, and marketing. Job requirement overlap can create opportunities for workers to transition between different occupations or industries, particularly when there are labor shortages in these occupations. For instance, when a particular occupation is experiencing a shortage of workers, it may be difficult for employers to find qualified candidates to fill open positions. In this case, individuals who have skills and experience in a related occupation may be able to transition into the in-demand field (Gathmann & Schönberg, 2010)

There is little systematic empirical research on what determines occupational transitions, although there are important candidates such as job requirement overlap and labor market tightness. One possible reason is high data requirements. One cannot simply use observed occupational transitions to study the boundaries. Observed transitions represent an equilibrium outcome that is determined by both firms and workers. A worker may desire to change to a new occupation and may even have the skills and experience to change to that occupation, but firms may be unwilling to hire her, for instance, because there is an ample supply of workers that already work in that occupation. Firms may actually be willing to hire the person, but workers may be unwilling or may not realize the opportunities. Indeed, recent interventions aim to increase job-seekers' occupational search scope and help them find jobs, reaching ambiguous conclusions. Belot et al. (2018, 2022) find that increasing occupational scope helped the long-term unemployed to obtain more job interviews, find a stable job and reach a cumulative earnings threshold. However, Dhia et al. (2022) found that an online platform designed to provide job search tips and recommendations had modest effects on search methods but no effect on short- or medium-term employment outcomes. Klaauw & Vethaak (2022)'s study suggests that formal policies that restrict job search opportunities may negatively affect labor market outcomes. So to study the determinants of occupational transitions, and eventually, to think about targeted job search advice, you optimally have data from both sides of the market and you optimally have an objective measure of workers' skill set that is independent of firms' (observed) hiring choices.

This paper provides empirical evidence on the extent to which recruiters seeking to fill a vacancy in an occupation are willing to consider only the resumes of job-seekers who have been working in the same occupation or whether they consider workers with experience in different occupations as well. Conversely, we also study the extent to which job-seekers who have been active in an occupation are searching for jobs in the same or different occupations. The patterns of clicks of job-seekers and recruiters on a large online labor market platform in Switzerland provide key insights into the underlying preferences and constraints that shape worker mobility across occupations. Using this data, we identify to what extent wages and work experiences shape the willingness to cross occupational boundaries of job-seekers and firms. Also, we study whether firms are more likely to recruit among other occupations when they experience labor shortages and whether job-seekers confine their search to their current occupation when there is a shortage of this occupation. Overall, studying the matching between employers and job-seekers across occupational boundaries can help policymakers and researchers develop more effective strategies for supporting workers who wish to change occupations.

We then study whether recruiters and job-seekers are willing to consider job-seekers who have not worked in the target occupation, and if so, to what extent job requirement overlap is driving interest on the firms' side. We also analyze how job search across occupational boundaries is shaped by labor market tightness.

A key implication of our analysis is that the labor supply facing a firm's vacancy is not limited to the number of job-seekers in the desired occupation.[1] Indeed, if job-seekers are willing to switch occupations, the pool of available workers increases, making it easier for employers to find the talent they need to fill their open positions. Labor demand facing each job-seeker is also potentially larger than the set of vacancies that invite applications from job-seekers with the listed occupation (Schubert et al., 2020). Again, a job-seeker may find work faster when considering a larger number of positions than when focusing on the desired occupation. Whether recruiters cross occupational boundaries, and whether job-seekers are prepared to look for positions outside their current occupation, are important research questions.

This paper is related to a number of strands in the literature. First, the literature that studies a firm's demand for workers using job postings data (Colella, 2022), and more recently search on online job boards (Lehmann, n.d.; Altmann et al., n.d.). Second, a literature that studies career transitions using resumé data (Schubert et al., 2020). Third, but more distant, the tasks based approach to occupations (Autor, 2013; Lazear, 2009; Gathmann & Schönberg, 2010; Robinson, 2018).

This paper is organized as follows. The next section provides a simple conceptual framework that organizes our analysis. Section 3 details how we measure the closeness between occupation, based on job requirements listed in job vacancies and how they overlap between occupations. Section 4 shows how recruiters search across occupational boundaries. Section 5 shows these results for job

[1] Manning & Petrongolo (2017) study job search and vacancy filling across the United Kingdom.

seekers and contrasts them with actual transitions. Section 6 summarizes our findings.

2 Conceptual Framework

We discuss a simple conceptual framework that provides a guideline to our analysis. The framework builds on the observation that recruiters and job-seekers must first acquire information on the counter-party before applying for a job, or inviting a job-seeker to a job interview. The analysis has three elements.

First, recruiters post a vacancy on an online platform that lists a target occupation and a set of job requirements. Let o denote the target occupation's ISCO code. Recruiters then see a list of candidates and decide on whom to invite for a job interview. We assume that recruiters contact candidates if the candidate is likely to be able to perform well on the job. To infer whether a candidate will perform well on the job, recruiters rely on several pieces of information that are commonly available to them. A first piece of information is the occupation that the job seeker has previously been employed in, let l denote a job-seeker's last or previous occupation. Employers will be able to infer whether a candidate should be invited for a job interview if the previous occupation l provides good information on the target occupation o. This will be the case if occupation o and l have are 'similar' in terms of their job requirements. We discuss in the next section 3 how we measure similarity.

Several other pieces of information are available to recruiters that could play a role in whether they access the contact details of candidates to invite them for an interview. Work experience in an occupation provides information on how much occupation specific human capital a job seeker has acquired (Gathmann & Schönberg, 2010). Also, the relative wage paid in an occupation compared to the target occupation could be a relevant determinant of whether employers contact job applicants.

The probability that a candidate with last occupation l will fit a target occupation o is

$$p_R^I(o|l)$$

The super-script I refers to the decision of acquiring information, the sub-script refers to the recruiter R. Our objective is to provide an empirical description of this probability that recruiters seeking to fill an occupation o contact job seekers in occupation l as a function of overlap between these two occupations, work experience in the previous occupation, and relative wages in the occupations.

Second, job-seekers who are active on the platform inform themselves on a job if the value of holding the job, compared to remaining unemployed one more period, times the probability of being invited (and eventually hired) on the job is greater than their information cost (c). For job seekers, the probability of being considered by the firm enters this consideration, but also the value of a job. Let V_o denote the present value of holding a job in occupation o, while U_l is the present value of remaining unemployed as a job seeker with previous occupation l. The probability that a job-seeker with last occupation l will access information on a target job o is given by

$$p_U^I(o|l) = Prob(p_R^I(o|l)(V_o - U_l) > c)$$

where the subscript U refers to the job seekers seeking information on a job vacancy. In principle, the probability that a job seeker with last job l is considered by a recruiter with target occupation o is the same as we identified for recruiters looking for job seekers.

Third, so far we have accessed indicators of labor demand and supply across occupations, e.g. clicks on online job search boards. One could argue that simple clicks may not represent actual decisions (Jarosch & Pilossoph, 2018). We provide an analysis of the determinants of a job-seeker moving from occupation l to occupation o. We assume that a move will occur if the job seeker gets invited to a job interview, expressed by $p_U^I(o|l)$, and if the job interview is successful. The job interview will be successful if the candidate fulfils the actual job requirements, whereas the decision to interview a candidate is based on an ex-ante assessment of the probability of fulfilling the requirements. So there can be important differences between online search behavior and actual transitions between occupations. Let the probability that a job seeker from l satisfies the job requirements of a specific job in occupation o is $h(o|l)$. We denote the likelihood that a job seeker moves from occupation l to an occupation o as

$$p_R^H(o|l) = h(o|l)p_U^I(o|l)$$

Note that the platform we study presents information to recruiters and job seekers in different ways. Recruiters see a list of candidates that is composed of job-seekers who are actively looking for jobs in the target occupation. This means that the set of job-seekers is already pre-selected to match the target occupation better than a randomly selected job-seeker would match. In this context, we would expect that the likelihood of contacting candidates is higher than in an alternative environment without pre-selection (as we have it for job seekers). In contrast, job seekers see the universe of job vacancies and need to filter it using their search criteria, e.g. occupation, but also work experience. This means that, unlike recruiters, job seekers are not entirely sure whether recruiters would consider their job application.

We organize our analysis along this (simple) conceptual framework. We first study the decisions of recruiters to access the contact details of candidates. We are particularly interested in how this decision varies with the overlap in job requirements between the target occupation and the last occupation of a job-seeker. We study which vacancies job-seekers look into, in a second step, because these decisions are shaped by both, the probability of being a good match for the job, and its value. We learn how recruiters and job-seekers clicks shape the patterns of job-seeker transitions across occupations.

3 Measuring Similarity

3.1 Data

We use job requirements data from a near-universe of online vacancies in Switzerland posted on job boards and firm websites between 2016 and 2022 to measure similarity of occupations.[2] These data are collected by the private company x28 AG and cover at least 72% of all vacancies and at least 90% of all vacancies posted online (Bannert et al., 2022).[3] Overall, our sample contains 2'117'082 vacancy postings. Bannert et al. (2022) show that the industry and regional composition is very similar as in vacancy and employment data from official statistics. The data contain detailed information on every job posting, for instance, the creation and deletion date, the job title, industry and occupation identifiers, firm identifiers, information on the required work experience or education certificate, and the number of hours. Importantly, it also contains a detailed classification of all job requirements mentioned in the text of the job ad. In particular, the data distinguishes between 2'775 distinct skills or tasks. Examples of such job requirements include accuracy, commercial understanding, sales skills, team orientation, or different IT skills (e.g. knowledge of python). We use this classification to construct a continuous measure for job requirement overlap between the different occupations.

[2] Colella (2022) first used job postings data to analyze the effects of trade on labor demand using job postings.

[3] x28 continuously crawls job postings from all major online job boards in Switzerland and from company websites, identifies duplicate job postings and systematizes each job posting, for instance by assigning it to official industry and occupation classifications (Bannert et al., 2022).

3.2 Job Requirements Overlap

Formalizing the similarity of occupations is not a straightforward task. We, therefore, pre-registered a menu of possible ways to measure the closeness of vacancies (Klaeui et al., 2022). We then evaluate the performance of the overlap measures. We report analyses that use a version of job requirement overlap that performs best to discriminate between occupations, as we pre-registered in our pre-analysis plan.

The preferred measure calculates the overlap in the demand for each job requirement in two occupations relative to total demand for skills, using a weighted Jaccard distance. Specifically, the job requirement overlap between occupation o, the target occupation, and l the last occupation (of a job-seeker), uses information on $s_{i,o}$, the share of job ads in occupation o that list job requirement i. Using this information, we construct the (weighted) Jaccard index

$$J_{o,l} = \frac{\sum_{i \in Requirements} min(s_{i,o}, s_{i,l})}{\sum_{i \in Requirements} max(s_{i,o}, s_{i,l})}$$

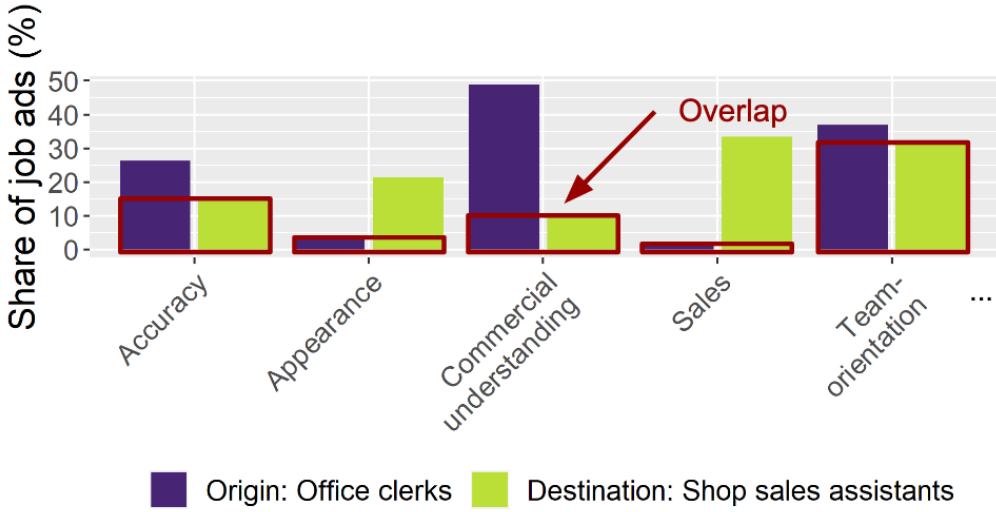
Intuitively, the measure captures the similarity in the job requirements profile of all vacancies from two different occupations.[4] Job requirements overlap is a continuous measure of the overlap between occupations and allows us to provide fine grained insights into the nature of labor demand and supply across occupational boundaries.

Figure 1 provides an illustration of the degree of job requirement overlap between two occupations: office clerks and shop sales assistants. The figure highlights that there is a high degree of overlap in terms of the skill "accuracy," which is indicated by the red box. This indicates that both office clerks and shop sales assistants require a high level of accuracy in their work. However, in terms of the skill "sales," the overlap is relatively low, which suggests that the level of expertise required for sales may be different for these two occupations. Overall, this figure highlights how skills can vary in relevance and importance across different job roles and occupations, and how understanding these differences can be helpful in identifying the right candidates for a given job.

In Figure 2, we can observe the distribution of the similarity index between different occupation tuples based on their skill requirements. It is evident that some occupations, such as office clerks and secretaries, have a high degree of skill overlap, indicating that they share many common job requirements. On the other hand, occupations like office clerks and messengers show a low overlap in skills, suggesting that they require vastly different skill sets. However, most of the occupation tuples display an intermediate level of job requirement overlap, indicating that they share some

[4] Colella (2021) uses the Jaccard index to define similarity of soccer teams.

Figure 1: job requirement Overlap Example



Notes: This figure illustrates job requirement overlap between two occupations: office clerks and shop sales assistants.
Source: Own calculations based on X28 vacancy data.

common skills while differing in others. Overall, it is rare to find occupation tuples with either small or great overlap in job requirements.

4 Recruiters: Labor Demand Across Occupations

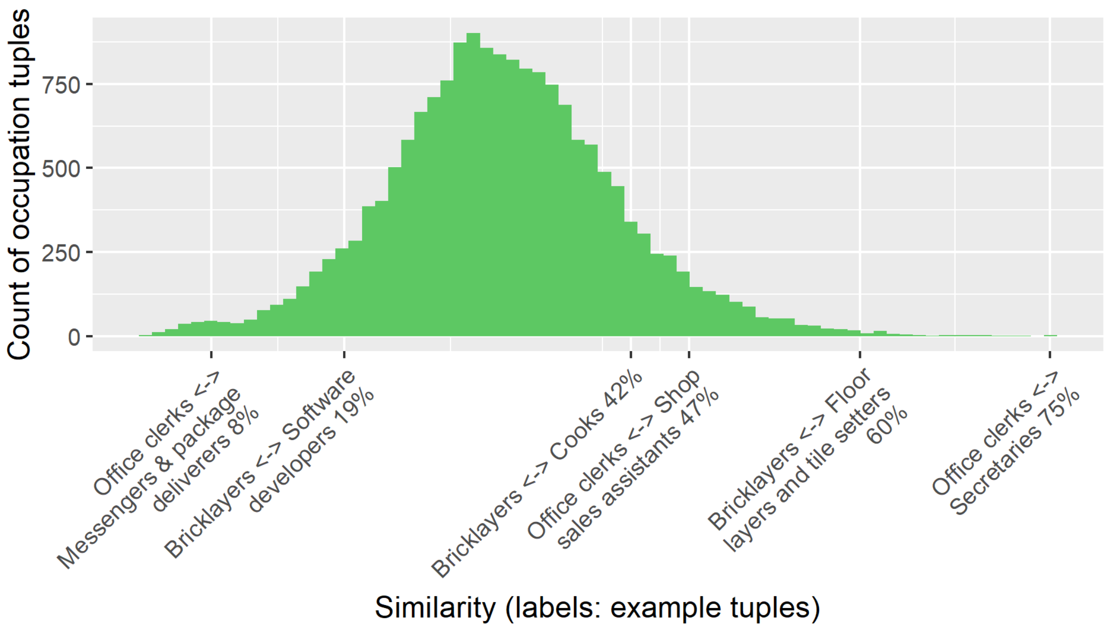
4.1 Data

Our data on recruiter search activity is recruiter click data from the platform job-room.ch, which is maintained by the State Secretariat for Economic Affairs. On that platform, recruiters can search for candidates by entering desired occupation and other search criteria. They then see a feed that is, essentially, a list of candidates, all of which have at some point worked in the desired occupation or stated that they are looking for a job in the desired occupation. Clicking on a candidate provides further information on the candidate (Figure 7 in the Appendix). For our purposes, the most important information concerns the occupations in which the job-seeker is looking for jobs, and her or his work experience in the respective occupations. The first occupation that is listed is the occupation the job-seeker was active in most recently. Other information on the job-seeker profile comprises language skills, education certificates, gender, etc. Recruiters can then access the contact details of the candidate by clicking on a "Show Contact Details" button.[5] The "click" decision we analyze is a click on the contact button.

We use click data on recruiters from the period from March to December 2017 to assess the labor demand facing a job-seeker. During that period, 33'216 recruiters conducted a total of 317'123

[5]Hangartner et al. (2021) show that contact clicks predict exit of unemployment.

Figure 2: Job requirement Overlap Between Occupations



Notes: This figure reports a histogram of job requirement overlap between all tuples of occupations.
Source: Own calculations based on X28 vacancy data.

Table 1: Descriptive statistics on recruiter clicks.

	All observations	Last occ.= searched occ.	Last occ. $\neq$ searched occ
N recruiters	33 216		
N searches	317 123		
N jobseekers	173 638		
Mean N occupations listed per jobseeker	2.5	0.95	1.55
N profile views	2 905 207	1 647 204	1 258 003
Contact button click probability (%)	43.09	46.1	39.16

searches and visited 2'905'207 times a candidate profile (see Table 1). Our main dependent variable is a binary indicator called click, which is one if the recruiter clicks to get the contact details of a job-seeker and zero otherwise. The probability of accessing the contact details is 43%, conditional on viewing the profile. Hence, the first selection step, when recruiters decide which profiles to access from the list, is already quite precise. Note, that the occupational information is only visible after a recruiter opens a profile, the viewing decision is therefore based on other factors. The recruiters face a population of 211'572 job-seekers who on average list 1.35 occupations in addition to the last occupation. In 57% of the profile views, the job-seekers' last job was in the advertised occupation (see Table 1). Conversely, in 43% of the profile views, a job-seeker worked previously in a different occupation than the one in which recruiters are searching for candidates.[6] All analyses control for recruiter search fixed effects, and rank of profile effects.

4.2 Recruiter Search

On the platform, recruiters have the ability to find potential candidates by inputting the preferred occupation and other relevant filters. This generates a feed displaying a selection of individuals who have either previously worked in the targeted occupation or expressed interest in doing so. By opening a candidate's profile, recruiters can access additional details about them. We estimate the probability that a recruiter - after having seen a job-seeker's profile - clicks on a button to see the candidate's contact details. We use a linear probability model (eq. 1) with job-seeker and recruiter-search fixed effects. Recruiters see job-seekers who have last worked in the occupation they search in but also candidates who have last worked in a different occupation but stated their willingness to work in the searched occupation. This creates variation in the searched occupation of the searches a job-seeker appears in. We can use this variation to identify the effect of the occupational similarity between the job-seeker's last occupation $l(i)$ and the occupation of the search, $o(s)$, while controlling for all job-seeker specific characteristics with the job-seeker fixed

[6] Job-seekers can appear on the search lists of recruiters if the advertised occupation matches one of the occupations listed by the job-seekers.

effect, α_i. The search fixed effect, ϕ_s allows us to directly compare candidates appearing in the same search and also controls for all recruiter-specific effects. We further control for experience in the searched occupation a candidate might have gathered prior to working in her last occupation ($exp_{i,o(s)}$). We measure the similarity between the job-seeker's last occupation and the searched occupation using a set of dummies indicating the overlap in job requirements as well as dummies indicating differences in the median wage level between the two occupations ($dwage_{i,o(s)}$). We control flexibly for the absolute rank and the relative rank of a jobseeker within the list of search results.

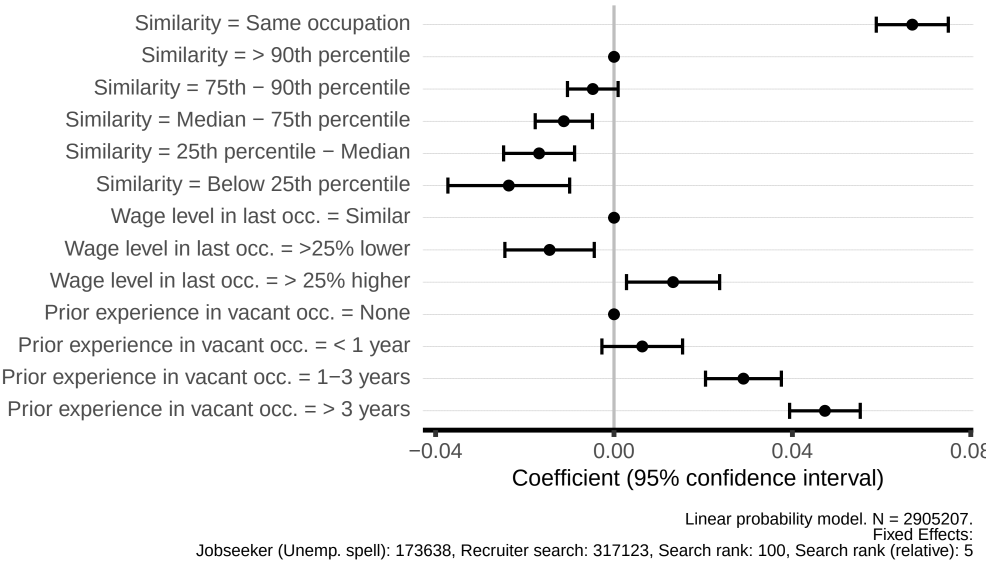
$$y_{i,s} = similarity_{l(i),o(s)} + dwage_{l(i),o(s)} + exp_{i,o(s)} + \alpha_i + \phi_s + \psi_{rank(i,s)} + \varepsilon_{i,s} \tag{1}$$

Recruiters are much more likely to click on candidates who have worked in the desired occupation (Figure 3)[7]. Job-seekers who last worked in the same occupation as the one recruiters are looking for are roughly seven percentage points more likely to be contacted than the baseline, which refers to vacancies contacting job-seekers who last worked in an occupation with high degree of job requirement overlap with the desired occupation (job requirement overlap is larger than the 90th percentile). The likelihood that recruiters contact job-seekers decreases monotonically as the job requirement overlap between the posted occupation and the job-seeker's last occupation decreases. Job-seekers with previous occupation that has the least overlap are 2 percentage points less likely to be contacted, compared to the baseline. Even though job requirement overlap plays a role, there is a strong tendency to be interested in job-seekers who work in the stated occupation. This suggests that skill overlap plays a role but having worked in the same occupation as the one a recruiter is looking for has a (signalling) value that exceeds the benefits from a large fit in skill requirements. One reason for this pattern in labor demand could be boundaries between occupations which are not captured by the overlap measure, e.g. job requirements for diploma etc. which may not be listed in the job vacancy.

Job seekers with some work experience in the advertised occupation at some point in the past helps to get contacted by recruiters. Job seekers with 1-3 years of experience are about 3 percentage points more likely to be contacted by a recruiter, and those with more than 3 years are 4.5 percentage points more likely to be contacted, compared to having no experience, or less than one year experience. The click pattern is monotonically increasing in the number of years worked in the occupation. However, even quite long past work experience in the target occupation can

[7] Table 4 in the Appendix shows the results in table form.

Figure 3: Labor Demand Across Occupations



Notes: The baseline probability of requesting contact details for a candidate is 0.43. Estimates are based on linear probability models which control for search fixed effects, job-seeker fixed effects.
Source: Own calculations, job-room data.

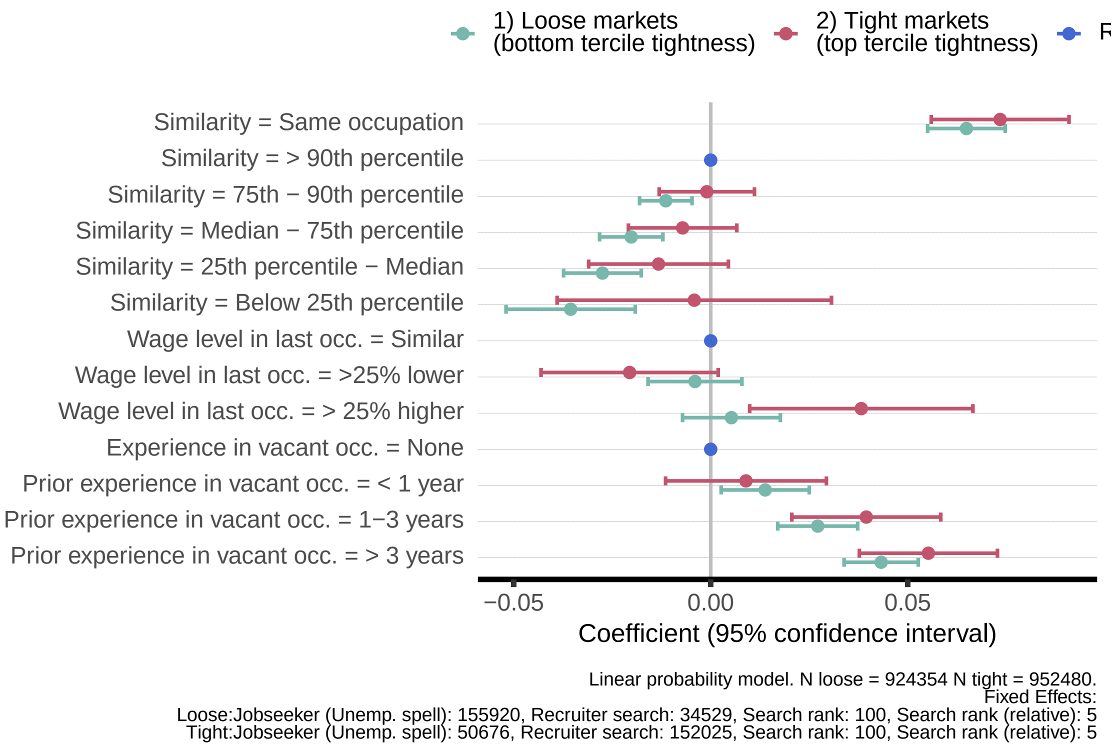
not make up for the benefit of having worked previously in the same occupation, with an effect of almost 8 percentage points increase on the click probability.

Recruiter's behavior is also sensitive to relative wages (Figure 3). We use occupational median wages from the Swiss Earning Structure Survey for each occupation to capture the wages paid to workers in different occupations. Recruiters are less likely to request contact details of job-seekers who worked in lower wage occupations, those that paid at least 25% lower wages than the advertised occupation, compared to job-seekers with similar wages. In contrast, recruiters were more likely to contact job-seekers in higher wage occupations, those that paid at least 25% more than the desired occupation, relative to job-seekers in occupations paying a similar wage. These results suggest that the recruiters attempt to attract job-seekers from higher paid occupations, while they are reluctant to do so for lower paid job-seekers.

Recruiters are looking to fill vacancies in very different occupations, some with labor shortages and some with excess supply of workers, so market tightness differs across occupations. We measure occupation market tightness on the job-room recruiter platform by calculating the ratio of similar recruiter searches to the number of candidates in a search.[8] The larger the ratio, the tighter the respective sub-market. Recruiters in tight markets tend to increase labor demand for job-seekers outside the advertised occupation (Figure 4). Specifically, recruiters in tight markets, compared to

[8]To compute this ratio, we consider only candidates with the same last occupation as the occupation searched. The number of candidates is determined by the number of results a search yields, while the number of similar searches is determined by the frequency of appearance of the average candidate in the result list during the 30 days preceding the search.

Figure 4: Labor Demand in Tight and Slack Markets



Notes: The baseline probability of requesting contact details for a candidate is 0.43. Estimates are based on linear probability models which control for search fixed effects, job-seeker fixed effects. Tight markets are those with tightness exceeding the median tightness. Slack markets (loose markets) are the remaining markets.
Source: Own calculations, job-room data.

Table 2: Descriptive statistics on job-seeker clicks.

	All observations	Last occ.= vacancy occ.	Last occ. $\neq$ vacancy occ
N jobseekers	131 371		
N clicks	7 501 392	1 986 917	5 514 475
Mean clicks per jobseeker	57.1	15.12	41.98

those who recruit in slack markets, are more likely to contact job-seekers who have not worked in the posted occupation, and this regardless of their previous occupations' overlap with the posted occupation in the vacancy. In contrast, recruiters become more selective in terms of the relative wage and in terms of work experience. The difference in the contact probability between the candidates working in higher (than the stated vacancy) paid vs lower (than the stated vacancy) paid occupations are large and significantly different from zero, whereas this difference is not significant in slack markets. In tight markets, recruiters are more likely to request contact details on candidates who have at last some work experience in the occupation, compared to slack markets. Occupation market tightness tends to increase the experience gradient. In sum, recruiters in tight markets are less selective in terms of fit with the position but more selective in terms of experience and aspects captures by the occupation wage.[9]

5 Job-Seekers: Labor Supply Across Occupations

5.1 Data

To measure the labor supply facing a vacancy we use also data from the government platform job-room. We measure job-seekers' interests in job postings using their clicks on vacancies. [10] Specifically, we have data on job search behavior of registered job-seekers for the period June 2020 to June 2021. There are a total of 131'371 job-seekers in our sample who on average click on 57 vacancies (see Table 2). We know the occupation (ISCO-08 4-digit level) of each vacancy and the last occupation of each job-seeker. For every month with at least one click we aggregate a job-seeker's clicks on the occupation level.

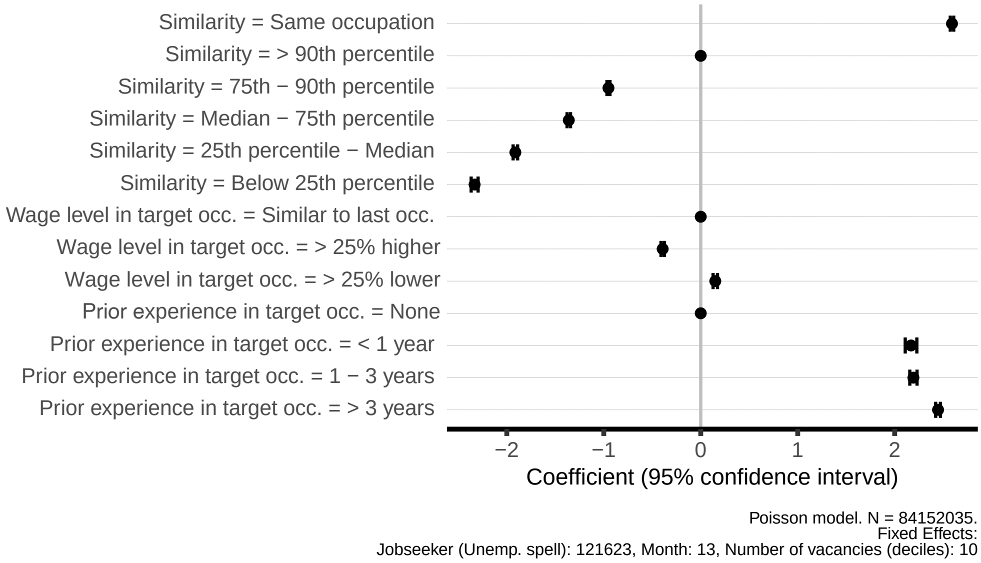
5.2 Job Search Across Occupations

We analyze how job-seekers distribute their clicks over the occupations. The outcome $y_{i,t,o}$ is the number of clicks that job-seeker i makes on vacancies in occupation o in month t. The explaining variables are the overlap in job requirements between the job-seekers last occupation and the target

[9] Modestino et al. (2020) find that skill requirements increase when firms face a larger pool of applicants.

[10] Bassier et al. (2023) use similar data to study monopsony power of firms.

Figure 5: Labor Supply Across Occupations



Notes: This figure shows an analysis of how many times a job-seeker clicks on a vacancy. Estimates are based on Poisson regression models, which controls for job-seeker fixed effects, month fixed effects and the number of vacancies available on the platform in every month-occupation cell.
Source: Own calculations, job-room data.

occupation $similarity_{l(i),o}$ as well as whether the job-seeker already has experience in occupation o. We distinguish between experience from the most recent job - in which case $l(i) = o$ - and potential experience from earlier career stations ("prior experience", $experience_{i,o}$). We further look at the effect of differences in the median wage level between a job-seeker's last occupation and the target occupation ($dwage_{l(i),o}$). We adopt a Poisson regression that controls for a job-seeker fixed effect, α_i to analyze clicks on vacancies by job-seekers. The job-seeker fixed effect absorbs differences in click rates and average distance to other occupations. We further control flexibly for the number of vacancies available on the platform in every occupation-month-cell, $X'_{i,o}\beta$ and a calendar month fixed effect, θ_t.

$$log(E[y_{i,t,o}]) = exp(similarity_{l(i),o} + dwage_{i,o} + experience_{i,o} + X'_{i,o}\beta + \alpha_i + \theta_t) \qquad (2)$$

The labor supply facing a vacancy decreases strongly as the skill overlap between their last occupation and the target occupation decreases (Figure 5)[11]. Job-seekers are much more likely to click on vacancies from the same occupation as their last job, compared to vacancies from other occupations. This "same vacancy" effect appears much stronger for job seekers than for recruiters, but bear in mind that recruiters only see a list of candidates that is already pre-filtered and contains

[11] Table 6 in the Appendix shows the results in table form and compares them to a specification including target occupation (o) fixed effects

only candidates who are looking for the target occupation. Job seekers can potentially see all job ads, so it is not surprising that the *same occupation*-effect is stronger for job seekers.

Job-seekers are less likely to click on vacancies that overlap less with their previous occupation, compared to the vacancies that are most similar to their last occupation. The probability that job seekers click on vacancies decreases monotonically and again more strongly than for recruiters (Figure 3). The dissimilarity decline of interest among job seekers is probably due to two factors, the declining interest on the part of recruiters, $p_R^I(o|l)$, but also a decline in interest and motivation from the job seeker, $V_o - U_l < 0$ (Section 2).

The relative median wage offered in an occupation is a second important determinant. Somewhat surprisingly, job-seekers are more inclined to click on jobs from occupations with a lower wage level than their current occupation. However, this behavior mirrors the behavior of firms which are more likely to contact job-seekers from occupations with a higher wage level (Figure 3). Conversely, job-seekers are less likely to click on vacancies from occupations with a higher wage level, and this is again consistent with the behavior of firms. Experience in the target occupation of the vacancy is an important and essential factor that significantly impacts the job-seekers' clicking behavior, particularly when they have some experience, compared to no experience.[12]

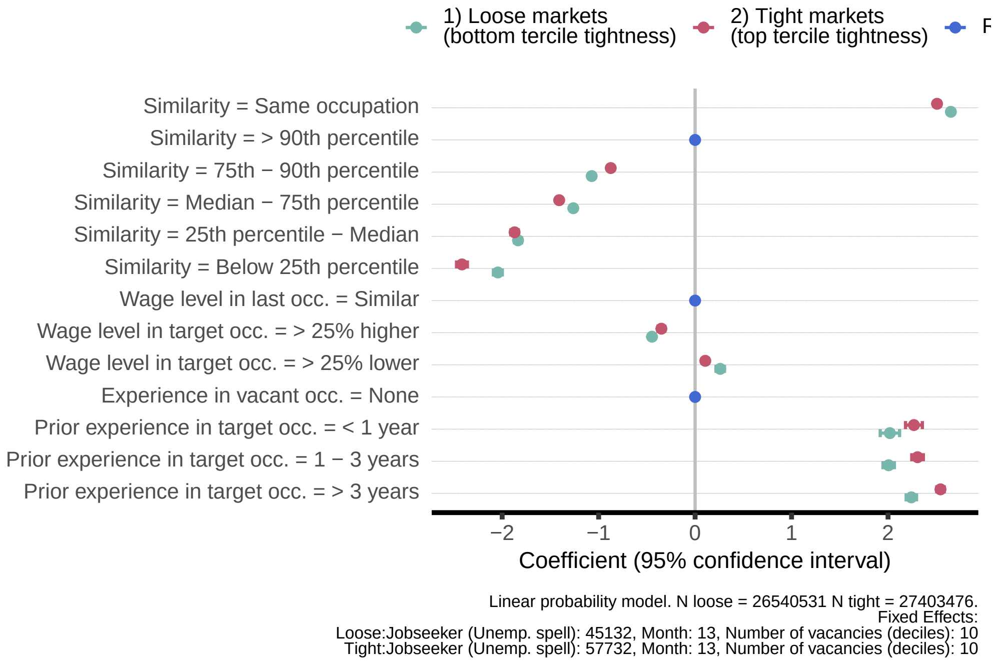
We now present results by occupation market tightness for job-seekers (Figure 6).[13] Job-seekers in a tight occupation market, with many vacancies compared to the number of clicks on the job ads, are less likely to click on job ads that have very little overlap with their previous occupation, so they are less likely to cross occupational boundaries. While firms become less picky in terms of occupational fit in tight labor markets, job-seekers become more picky. This makes sense. Tight labor markets imply fewer alternatives for firms, hence they cannot afford to be picky. On the other hand, it means more alternatives for job-seekers. Hence, they can be pickier than in slack markets.

Differences in the wage offered in the target occupation compared to the last occupation become somewhat less important in tight markets, but the difference is less important than for recruiters (Figure 4). One reason why job-seekers seem to be more inclined to target higher-wage occupations when the market is tight, is that they also consider their chances of getting the job. This is consistent with the predictions of our theoretical framework (see Section 2). We also find that job-seekers

[12]Appendix Table 5 shows results for two additional outcomes: whether a job-seeker states that they are willing to work in an occupation in the first meeting with the case worker and, for those using job-room.ch, whether they clicked on at least one vacancy posting in an occupation

[13]We measure market tightness as the ratio of ads to clicks by all other job-seekers in a given occupation-commuting zone-month cell. We exclude a job-seeker's own clicks from the count. Only ads that receive at least one click in a month are considered. We use the clicks of all users on the platform, not just the registered job-seekers in our sample.

Figure 6: Labor Supply by job-seekers with a Last Job in Tight vs Slack Markets



Notes: This figure shows an analysis of how many times a job-seeker clicks on a vacancy. Estimates are based on poisson regression models which control for search fixed effects, job-seeker fixed effects. Tight markets are those with tightness exceeding the median tightness. Slack markets (loose markets) are the remaining markets.
Source: Own calculations, job-room data.

with some work experience in the target occupation are more likely to click on job ads in a different occupation in tight markets, compared to slack markets.

5.3 Accepted Jobs Across Occupations

We also look at the probability of taking up employment in a new occupation. We are interested in the probability of finding and accepting a job in occupation o conditional on being willing to work there.

5.4 Data

From the unemployment register data, we can obtain the occupation of the job found after a completed unemployment spell. 81 456 jobseekers in our sample have completed their spell and found a job. For 67 505 jobseekers we know the occupation of the new job. We construct a dataset where one observation is a jobseeker-occupation-tuple where for every jobseeker we include all the occupations they are willing to work in.

5.5 Accepted Jobs Across Occupations

Table 3 shows the results of a linear probability model where the outcome is whether job-seeker i finds a job in occupation o. Columns (1)-(3) condition on the job-seeker having stated willingness to work in occupation o in her caseworker meeting. Columns (4)-(6) condition on the job-seeker having made at least one click in occupation o. Columns (2) and (5) add flexible controls for the number of vacancies available on the platform in occupation o and Columns (3) and (6) include an occupation o fixed effect, absorbing all occupation-specific factors affecting the probability of finding a job.

The results are robust across specifications and show that, even conditional on a jobseeker showing a willingness to work in an occupation, the probability of actually finding a job in an occupation different from the last occupation is much lower. The conditional probability of finding a job in the last occupation is between 53% and 63%, depending on the specification.[14] At the same time, the probability of finding a job in any occupation with a high overlap in job requirements (above 90th percentile) is as low as 4%-8%. However, this is still substantially higher than the probability of finding a job in occupations with very little overlap (below 25th percentile), which is almost equal to 0.

	Conditional on stated interest in occupation			Conditional on at least one click in occupation		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	Found job in occ.	Found job in occ.	Found job in occ.	Found job in occ.	Found job in occ.	Found job in occ.
Similarity = Above90thpercentile	-0.6501*** (0.0047)	-0.6488*** (0.0047)	-0.6256*** (0.0051)	-0.6742*** (0.0040)	-0.6725*** (0.0040)	-0.6469*** (0.0042)
Similarity = 75th-90thpercentile	-0.6679*** (0.0055)	-0.6663*** (0.0055)	-0.6312*** (0.0059)	-0.6926*** (0.0038)	-0.6896*** (0.0038)	-0.6702*** (0.0040)
Similarity = Median-75thpercentile	-0.6668*** (0.0058)	-0.6662*** (0.0058)	-0.6316*** (0.0062)	-0.7004*** (0.0037)	-0.6959*** (0.0038)	-0.6784*** (0.0040)
Similarity = 25thpercentile-Median	-0.6783*** (0.0076)	-0.6777*** (0.0076)	-0.6535*** (0.0078)	-0.7025*** (0.0037)	-0.6968*** (0.0038)	-0.6812*** (0.0040)
Similarity = Below25thpercentile	-0.7274*** (0.0104)	-0.7260*** (0.0104)	-0.6894*** (0.0112)	-0.7080*** (0.0037)	-0.6999*** (0.0038)	-0.6888*** (0.0041)
Qualification relative to mode = Overqualified	-0.0464*** (0.0057)	-0.0570*** (0.0058)	-0.0471** (0.0193)	0.0020 (0.0014)	-0.0009 (0.0015)	-0.0036 (0.0023)
Qualification relative to mode = Underqualified	-0.0474*** (0.0072)	-0.0398*** (0.0072)	-0.0507*** (0.0196)	-0.0192*** (0.0013)	-0.0170*** (0.0013)	-0.0178*** (0.0023)
Number of vacancy postings = Quantile2		0.0544*** (0.0121)			8.5e-5 (0.0015)	
Number of vacancy postings = Quantile3		0.0490*** (0.0110)			0.0078*** (0.0016)	
Number of vacancy postings = Quantile4		0.0992*** (0.0107)			0.0243*** (0.0017)	
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------	------------------
Unemp. spell	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	No	Yes	No	No	Yes
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S.E.: Clustered	by: Unemp. spell	by: Unemp. spell	by: Unemp. spell	by: Unemp. spell	by: Unemp. spell	by: Unemp. spell
Observations	327,840	327,840	327,840	254,636	254,636	254,636
R2	0.75210	0.75272	0.76291	0.70721	0.70772	0.71155
Within R2	0.43957	0.44099	0.35880	0.43528	0.43626	0.40001

Table 3: Linear probability model whether a jobseeker finds a job in an occupation. Conditional on jobseekers for whom we observe the found job's occupation and for whom the found job is part of the set of listed / clicked occupations.

[14] This number is computed by taking the predicted probability for all the occupations in a similarity category and adding them up by category. This measurement accoutns for the fact that there is just one last occupation, while there are potentially many occupations in each overlap quantile and jobseekers can only start one new job

6 Summary

In summary, our research proposes a novel measure for occupational similarity that can aid in understanding search behavior on both sides of the labor market. Our findings suggest that recruiters have a significant preference for workers who have previously worked in the same occupation. However, skill overlap between occupations also plays a role. The smaller the overlap between two occupations, the lower the likelihood that recruiters contact job-seekers from other occupations. Looking at the other side of the market, job-seekers, too, tend to look for jobs in occupations that are similar to their previous one.

Moreover, recruiters in tight labor markets are more open to considering candidates from other occupations when the overlap is large. Workers in tight labor markets are less likely to cross occupation boundaries. So firms become less picky in terms of occupational fit in tight labor markets, while job-seekers become more picky. This makes sense. Tight labor markets imply fewer alternatives for firms, hence they cannot afford to be picky. On the other hand, it means more alternatives for job-seekers. Hence, they can be pickier than in slack markets.

Overall, our study highlights the importance of skill overlap between occupations, the acquired work experience in an occupation, labor market tightness and occupational differences in the wage level in determining the likelihood that job-seekers try to change occupations and that recruiters accept job-seekers from other occupations. By taking these factors into account, policymakers and employers can gain a better understanding of the preferences and behaviors of job-seekers and recruiters, respectively. This information can aid in the development of more effective job training and placement programs and help alleviate labor market frictions.

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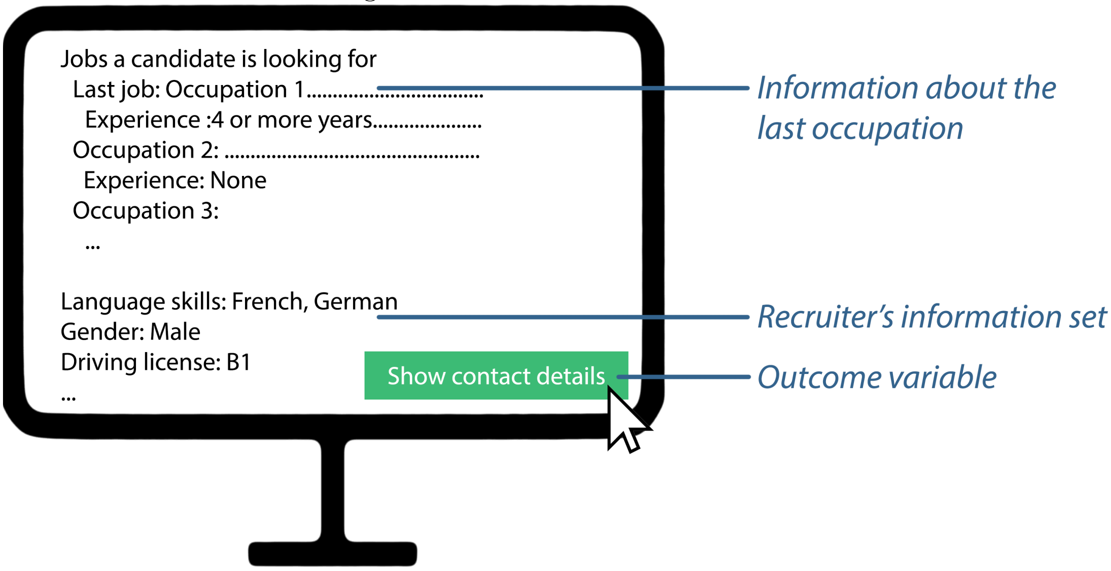
Appendix

Figure 7: Detailed Candidate View



Notes: This is a schematic representation of the search screen that recruiters see after clicking on a candidate in their feed. Recruiters who click on the green button 'show contact details' generate the click = 1 information. Recruiters who access the candidate view but do not click on the green button generate the click = 0 information. We use this information to infer the labor demand facing the job-seeker.
Source: Own design.

	models
Dependent Var.:	Contact button clicked
Similarity = Sameoccupation	0.0669*** (0.0041)
Similarity = 75th-90thpercentile	-0.0048 (0.0029)
Similarity = Median-75thpercentile	-0.0112*** (0.0033)
Similarity = 25thpercentile-Median	-0.0168*** (0.0041)
Similarity = Below25thpercentile	-0.0236*** (0.0070)
Wage level of last occ. = ¿25%lower	-0.0144*** (0.0051)
Wage level of last occ. = ¿25%higher	0.0132** (0.0053)
erfa_prior = ¡1year	0.0063 (0.0046)
erfa_prior = 1-3years	0.0290*** (0.0043)
erfa_prior = ¿3years	0.0473*** (0.0040)
Fixed-Effects:	———————-
Jobseeker (Unemp. spell)	Yes
Recruiter search	Yes
Search rank	Yes
Search rank (relative)	Yes
________________________________	____________________
S.E.: Clustered	by: Recruiter tracki..
Observations	2,905,207
R2	0.67116
Within R2	0.00074

Table 4: Linear probability model whether a jobseeker finds a job in an occupation. Conditional on jobseekers for whom we observe the found job's occupation and for whom the found job is part of the set of listed / clicked occupations.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	Listed	Listed	Listed	Clicked	Clicked	Clicked
Similarity = Above90thpercentile	-0.9407*** (0.0002)	-0.9401*** (0.0002)	-0.9341*** (0.0002)	-0.5200*** (0.0014)	-0.5098*** (0.0014)	-0.4629*** (0.0014)
Similarity = 75th-90thpercentile	-0.9439*** (0.0002)	-0.9429*** (0.0002)	-0.9366*** (0.0002)	-0.5893*** (0.0014)	-0.5697*** (0.0014)	-0.5160*** (0.0014)
Similarity = Median-75thpercentile	-0.9450*** (0.0002)	-0.9438*** (0.0002)	-0.9374*** (0.0002)	-0.6119*** (0.0014)	-0.5849*** (0.0014)	-0.5327*** (0.0014)
Similarity = 25thpercentile-Median	-0.9457*** (0.0002)	-0.9444*** (0.0002)	-0.9379*** (0.0002)	-0.6278*** (0.0014)	-0.5988*** (0.0014)	-0.5463*** (0.0014)
Similarity = Below25thpercentile	-0.9464*** (0.0002)	-0.9448*** (0.0002)	-0.9387*** (0.0002)	-0.6388*** (0.0014)	-0.6036*** (0.0014)	-0.5608*** (0.0014)
Qualification relative to mode = Overqualified	0.0023*** (2.23e-5)	0.0017*** (2.21e-5)	-0.0018*** (2.68e-5)	0.0174*** (0.0003)	0.0037*** (0.0002)	-0.0072*** (0.0003)
Qualification relative to mode = Underqualified	-0.0022*** (1.22e-5)	-0.0019*** (1.19e-5)	-0.0020*** (1.52e-5)	-0.0198*** (0.0002)	-0.0123*** (0.0002)	-0.0097*** (0.0003)
Number of vacancy postings = Quantile2		0.0001*** (5.26e-6)			0.0190*** (0.0002)	
Number of vacancy postings = Quantile3		0.0004*** (7.1e-6)			0.0391*** (0.0003)	
Number of vacancy postings = Quantile4		0.0033*** (1.16e-5)			0.0798*** (0.0004)	
Predicted # of listed / clicked occupations by spell (Counterfactual with no effect of similarity in parenthesis)						
Same occupation	0.95 (0.03)	0.95 (0.03)	0.95 (0.06)	0.65 (0.06)	0.65 (0.09)	0.65 (0.15)
Above 90th percentile	0.1 (0.15)	0.1 (0.21)	0.1 (0.23)	2.39 (0.95)	2.39 (1.31)	2.39 (1.58)
75th - 90th percentile	0.06 (0.2)	0.06 (0.23)	0.06 (0.25)	1.55 (1.31)	1.55 (1.49)	1.55 (1.56)
Median - 75th percentile	0.05 (0.31)	0.05 (0.3)	0.05 (0.3)	1.6 (2)	1.6 (1.92)	1.6 (1.92)
25th percentile - Median	0.03 (0.28)	0.03 (0.26)	0.03 (0.22)	1 (1.81)	1 (1.7)	1 (1.48)
Below 25th percentile	0.01 (0.26)	0.01 (0.19)	0.02 (0.18)	0.63 (1.61)	0.63 (1.25)	0.63 (1.07)
Fixed-Effects:						
Job seeker (unempl. spell)	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	No	Yes	No	No	Yes
S.E.: Clustered	by: Job seeker (un..	by: Job seeker (un..	by: Job seeker (un..	by: Job seeker (u..	by: Job seeker (u..	by: Job seeker (u..
Observations	177,396,073	177,396,073	177,396,073	18,893,653	18,893,653	18,893,653
R2	0.92078	0.92085	0.92175	0.24429	0.25875	0.28188
Within R2	0.74889	0.74911	0.74306	0.08440	0.10192	0.05592

Table 5: Linear probability model of two different outcomes: whether a job-seeker states that they are willing to work in an occupation in the first meeting with the case worker and, for those using job-room.ch, whether they clicked on at least one vacancy posting in an occupation

	(1)	(2)
Dependent Var.:	n_clicks	n_clicks
Similarity = Sameoccupation	2.591*** (0.0090)	2.305*** (0.0096)
Similarity = 75th-90thpercentile	-0.9518*** (0.0079)	-0.8956*** (0.0081)
Similarity = Median-75thpercentile	-1.361*** (0.0091)	-1.338*** (0.0096)
Similarity = 25thpercentile-Median	-1.912*** (0.0119)	-1.889*** (0.0129)
Similarity = Below25thpercentile	-2.332*** (0.0182)	-2.441*** (0.0245)
wage_diff_to_target = ¿25%higher	-0.3927*** (0.0087)	-0.1821*** (0.0117)
wage_diff_to_target = ¿25%lower	0.1500*** (0.0116)	-0.1085*** (0.0134)
Prior experience = 1-3 years	2.193*** (0.0190)	1.888*** (0.0193)
Prior experience = ¿ 3y	2.447*** (0.0125)	2.124*** (0.0131)
Prior experience = ¡1y	2.168*** (0.0306)	1.850*** (0.0299)
Fixed-Effects:	——————-	——————-
Jobseeker (Unemp. spell)	Yes	Yes
Month	Yes	Yes
Number of vacancies (deciles)	Yes	No
Occupation	No	Yes
----------------------------------	-------------------	-------------------
S.E.: Clustered	by: Jobseeker (Un..	by: Jobseeker (Un..
Observations	84,152,035	84,152,035
Squared Cor.	0.23994	0.26170
Pseudo R2	0.99944	0.99946
BIC	2,258,119.2	2,260,636.0

Table 6: Poisson regression of the number of clicks by occupation and month