Adapting to Scarcity: Job Search and Recruiting Across Occupational Boundaries

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Abstract

We analyze how overlap in job requirements and labor market conditions affect recruiters' and job seekers' search across occupational boundaries. We leverage unique click data from a job and recruitment platform linked to Swiss unemployment register records. We develop a novel measure of occupational similarity that quantifies the overlap in job requirements in vacancy postings between and within occupations. Overlap strongly determines job seekers' clicks on jobs in other occupations and recruiters' contacts of candidates from other occupations. However, job seekers' last occupation is also important. Job seekers and recruiters are substantially more likely to focus on jobs or candidates in the same occupation than in other occupations with the same overlap. Finally, the importance of the last occupation varies with scarcity. If tightness in an occupation increases, job seekers are less likely to consider switching occupation while recruiters are more inclined to contact candidates from other occupations, particularly those from similar, lower-paying occupations. A key novelty of these analyses is to demonstrate recruiters' important role in moderating job seekers' ability to change occupations.

Keywords: occupations, mobility, job requirement overlap, labor demand, labor supply.

JEL Codes: J24, J62, J63, J64

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1 Introduction

The capacity of workers to switch occupations is key for their ability to adapt to shocks and structural changes in labor demand. It enables workers to transition to new roles and industries that are experiencing growth or labor shortages, thereby contributing to structural change in the economy (Acemoglu & Autor, 2011). High occupational mobility can significantly reduce overall unemployment (Şahin et al., 2014; Herz & Van Rens, 2020) and dampen the negative effects of layoffs, automation, and employer concentration on workers' subsequent employment and wages (Bloesch et al., 2022; del Rio-Chanona et al., 2021; Gathmann & Schönberg, 2010; Robinson, 2018; Carrillo-Tudela & Visschers, 2023; Macaluso, 2023; Schubert et al., 2024)

Existing work documents occupational mobility mainly from a worker's perspective (e.g., Gathmann & Schönberg, 2010; Cortes & Gallipoli, 2018; Yamaguchi, 2012), even though employers are central to the phenomenon. Are employers willing to contact candidates even though their occupational fit with a position is less than perfect? How much weight do they place on an applicant's last occupation, and are employers willing to lower this weight when facing labor shortages? Do recruiters counteract job seekers' search behavior? While workers have incentives to remain in occupations with many job openings per worker, recruiters in such occupations may be more receptive to workers from other occupations. One likely reason for the lack of answers to these questions is the absence of data on recruiters' search behavior.

This paper uses novel online click data from both sides of the labor market to estimate how imbalances in supply and demand in occupations affect job seekers' and recruiters' search across occupational boundaries. We use click data from job seekers from the job platform, of the Swiss Public Employment Service, Job-Room, to study what determines that registered job seekers look for jobs in a different occupation than their last one. We use click data from recruiters from the recruitment functionality of the same platform to analyze the determinants of whether recruiters seeking to fill a vacancy in one occupation contact registered job seekers who last worked in a different occupation. The analyses leverage that we can link job seekers' online profiles to the Swiss Unemployment Register. Thus, we know job seekers' last occupation, the occupations they previously worked in, as well as the occupations they consider when screening vacancies—what we term their occupational search scope. The analysis of the search behavior of recruiters also exploits that we have all the information about job seekers that recruiters see on Job-Room.

Our analysis is organized in three steps. We first construct a novel measure of occupational similarity based on the overlap in job requirements in online job postings. The task-based approach to labor markets emphasizes the role of overlap in task and job requirements for occupational transitions and suggests that human capital can at least partially be transferred to occupations where workers perform similar tasks (see, e.g., Lazear, 2009; Gathmann & Schönberg, 2010; Yamaguchi, 2012; Cortes & Gallipoli, 2018). We implement this idea empirically using data on extracted job requirements from the near-universe of online job postings in Switzerland. We randomly draw vacancy pairs from different occupations and estimate the proportion of job requirements that are present in both vacancies. Averaging over thousands of vacancy pairs, we estimate the average overlap between two occupations. A distinctive advantage of our similarity index is that, by drawing vacancy pairs from the same occupation, we can also estimate the overlap of job requirements within an occupation. Another advantage is that it is broadly applicable. Researchers with vacancy data and extracted job requirements can use it to construct context-specific measures of occupational similarity between arbitrary groups of vacancies.

Second, we quantify the relevance of job requirement overlap and job seeker's last occupation in determining search across occupational boundaries on both market sides. We first use our job-seeker click data to relate job seekers' occupational search scope to the index of job requirement overlap, holding other factors that could also influence workers' decisions, such as wage differentials, constant. We observe that occupations that have a 20% overlap in job requirements to job seekers' last occupations receive 15 times more clicks than occupations with an overlap of 10%.

However, our results are also suggest a key role of workers' last occupation. 31% of all job seeker clicks are in their last occupation. In fact, because we are measuring within-occupational similarity, we can benchmark the relevance of job requirement overlap against that of the last occupation. This comparison shows that job seekers are at least twelve times as likely to click on job ads in their last occupation than on job ads in a different occupation that has the same overlap in job requirements.

We then turn to recruiters' clicks on the recruitment platform and find evidence that candidates' last occupation matters substantially to recruiters, too. Among the job seekers that recruiters contact on the platform, 61% last worked in the exact occupation in which recruiters search for candidates (henceforth referred to as "recruiters' searched occupation"). We then isolate the causal effects of job seekers' last occupation on recruiters' contact rates by exploiting that the same candidates are found by recruiters searching in different occupations with varying similarity to the candidate's last occupation, which allows us to control for all observed and unobserved candidate characteristics. We find that job seekers who last worked in a recruiter's searched occupation have a 4.5% higher probability of being contacted than otherwise observationally equivalent job seekers who did not. This effect on the contact rate only compares job seekers with the same prior experience in recruiters' searched occupation. It is larger than the effect of having more than three years of work experience in an occupation compared to having none.

We also find that recruiters' contact decisions reinforce the importance of job requirement overlap for occupational transitions. Holding other candidate characteristics constant, recruiters contact 45% of candidates who last worked in an occupation that has 25% overlap with the recruiters' searched occupation. The contact rate is 41% for candidates who last worked in an occupation with 10% overlap.

Third, we demonstrate that job seekers and recruiters adjust their occupational search scopes in response to scarcity in a manner that aligns with economic intuition and that is efficiency-improving (Kircher, 2022). To show this, we relate job seekers' and recruiters' occupational search scopes to time-varying occupation- and region-specific measures of labor market tightness. These measures of labor market tightness are constructed using data covering the universe of job openings in an occupation-region and the universe of registered unemployed. Since they are based on external data, the measures are not mechanically related to tightness on the platform. To identify causal effects, the preferred job-seeker regressions leverage within-person changes in labor market tightness over the unemployment spell. The recruiter regressions exploit over-time variation in tightness between searches of the same recruiters in the same occupation and region.

On the job seeker side, we find that job seekers whose last occupation becomes tighter are more likely to target job ads that match their last occupation. We also find that tightness in the last occupation induces job seekers to click on occupations with more similar job requirements. If we differentiate between clicks that target a better-paying and a worse-paying occupation than job seekers' last occupation, we find that tightness reduces views of job ads in both higher- and lower-paying occupations.

On the employer side, we find that recruiters facing a tighter labor market become more willing to contact workers from other occupations, counteracting job seekers' increased focus on that occupation. Recruiters extend their occupational scope mainly to candidates from occupations that are relatively similar to the searched occupation. As we may expect, the effects are driven by non-regulated occupations—occupations that do not require a certain license to pursue it. In regulated occupations, there is no impact of tightness on recruiters' contact decisions. Recruiters in regulated occupations also have a substantially lower probability of contacting job seekers who last worked in a different occupation to start with. Unlike job seekers, tightness in a recruiter's searched occupation induces recruiters to switch mainly to job seekers from lower-paying occupations.

Our study contributes to several strands of literature. First, our analyses speak to a large literature on the specificity of human capital. In a seminal paper, Lazear (2009) argues that individual skills may be general, but combinations of skills are often specific to a particular firm. This implies that switching between firms with a similar skill mix is easier than switching between firms with little skill overlap. This framework has been extended to occupations. Several studies suggest that the transferability of skills between occupations is an important factor in explaining occupational transitions and their impact on labor market outcomes such as wages or re-employment opportunities (Poletaev & Robinson, 2008; Gathmann & Schönberg, 2010; Yamaguchi, 2012; Cortes & Gallipoli, 2018; Robinson, 2018; Goos et al., 2019; Macaluso, 2023; Bohm et al., 2024, among others). In line with this literature, we assume that occupations produce output through occupation-specific bundling of tasks associated with particular skills (Robinson, 2018). This implies that the degree of task and skill overlap between occupations is a crucial factor in explaining occupational mobility. Unlike other studies in the literature, we examine occupational transitions from both the perspectives of job seekers and recruiters.

We also contribute to the growing body of research on the occupational search scope of unemployed job seekers and its effect on their re-employment prospects. While Altmann et al. (2023) investigate the occupational scope of job seekers in Denmark descriptively, a number of recent studies evaluate interventions that provide job seekers with tailored occupational recommendations (Belot et al., 2019, 2022; Altmann et al., 2022; Dhia et al., 2022). The findings of these studies are ambiguous. Belot et al. (2019, 2022) suggest that at least some groups of job seekers benefit from such interventions, while Dhia et al. (2022) find no effect on short- or medium-term employment outcomes. van der Klaauw & Vethaak (2022) found that mandatory requirements for registered job seekers to search more broadly may even decrease job finding. This shows that it is crucial to provide job seekers with the *right* occupational recommendations. Such recommendations should meet at least two requirements: Job seekers should have the skills to work in the recommended occupation, and there should be jobs available there (Kircher, 2022).[1] Our study can help to improve recommendations along both dimensions. On the second dimension, we provide insights into the extent to which job seekers and recruiters are adapting to scarcity in occupations, which can help to better understand whether and how potential interventions should take competition into account. On the first dimension, we develop a new measure of job requirements overlap that can

[1] Altmann et al. (2022) provide evidence on the importance of the latter. Based on a large-scale randomized controlled trial among the universe of unemployment benefit recipients in Denmark, they find that occupational recommendations are effective only when the share of treated workers is relatively low. At higher treatment intensities, they find substantial negative spillovers on other job seekers.

help to identify occupations in which job seekers may find work.

We also contribute to a literature that develops measures of occupational permeability. Such measures are important not only for advising job seekers, but for any study that aims to define the boundaries of labor markets without relying on the simplified assumption that they are sharply defined by official occupational classifications. Several previous studies use observed occupational transitions as a measure of occupational distance (Schubert et al., 2024; del Rio-Chanona et al., 2021; Schmutte, 2014; Belot et al., 2019, 2022). Others use explicit measures of task overlap between occupations.[2] Again other studies use surveys among workers Gathmann & Schönberg (2010) or vocational education and training curricula Eggenberger et al. (2018). In contrast to these studies, our index of occupational distance is based on job requirements extracted from online job postings. Few other studies use this approach,[3] which allows for dynamic measurement of occupational similarity based on actual, up-to-date job requirements and is easily applicable to different contexts. In addition, the overlap of job requirements can be quantified not only between different occupations, but also within the same occupation.

By examining the effect of labor market tightness on the occupational search scope of job seekers and recruiters, we also provide a micro-foundation for the macro literature on mismatch unemployment after recessions (Şahin et al., 2014) and the cyclicality of occupational mobility (Moscarini & Thomsson, 2007; Carrillo-Tudela et al., 2016; Kambourov & Manovskii, 2008). Consistent with these studies, we find that labor supply and demand imbalances affect the extent to which job seekers and recruiters, respectively, search for job opportunities and candidates across occupations. While there are few other papers assessing how job seekers respond to local supply and demand imbalances by adjusting their occupational search scope (Altmann et al., 2023), we are the first to assess how recruiters' willingness to accept job seekers from other occupations is affected by the tightness in their occupation.

This paper is organized as follows. The next section 2 details how we measure the closeness between occupation based on job requirements listed in job vacancies and how they overlap between occupations. Section 3 details the recruiter and job-seeker click data that we link to unemployment register data. Section 4 shows how job requirement overlap shapes recruiters' and job seekers'

[2]Many of the latter rely on occupational skill classification systems such as the Dictionary of Occupational Titles DOT (Poletaev & Robinson, 2008; Yamaguchi, 2012; Cortes & Gallipoli, 2018; Robinson, 2018), its successor O*NET (Alabdulkareem et al., 2018; Belot et al., 2019, 2022; Macaluso, 2023; Lyshol, 2022), or the Operational Directory of Trades and Jobs ROME (Goos et al., 2019) to extract the tasks or skills that are particularly prevalent in an occupation.

[3]Another study is Leping (2009), which measures skill overlap between firms based on vacancies from the largest online job search platform in Estonia. However, while his measure is based on only three broad skill groups (computer, language, and driving skills), we use a very fine-grained measure of job requirements.

search across occupational boundaries. Section 5 estimates the effect of tightness in an occupation on the occupational scope of recruiters and job seekers in that occupation. Section 6 summarizes our findings.

2 Measuring the Overlap in Job Requirements

2.1 Conceptual Background

A key goal of this project is to quantify the importance of overlap in skills and tasks between and within occupations in explaining which occupations job seekers target and which occupational backgrounds recruiters consider. To this end, we build a new measure of the similarity of occupations based on job requirements extracted from job advertisements posted online. Job postings typically include a list of skill requirements for suitable candidates and often demand specific educational certificates and diplomas. In addition, they often detail the duties and tasks of the open position. A successful candidate likely has the experience and skills to perform these tasks. The combination of tasks, skills, and certificates listed on a job ad is what we refer to as "job requirements" henceforth.

Our approach to measuring occupational similarity builds on a small number of studies that propose to use job requirements from vacancies to measure the similarity of groups of jobs.[4] Our approach is also closely related to studies using explicit measures of occupational similarity based on the overlap in tasks or skills between occupations according to occupational skill classifications.[5].

Our approach has two main advantages over the use of task and skill dictionaries. First, it is a dynamic measure of task and skill overlap that is not bound to a specific location and time. Second, it allows us to measure the overlap in job requirements within occupations. Existing evidence, such as the high relevance of job titles for explaining job seekers' application behavior (Marinescu

[4] An early example is Leping (2009) who measures skill overlap between firms based on job requirements in vacancies from an online job-search platform in Estonia. A key difference of our relative to his measure is that our skill and task classification is much more granular. While our overlap considers thousands of categories, his measure only takes three broad skill groups into account (computer skills, language skills, and driving skills). Another related paper is Bloesch et al. (2022) who construct a measure of within-firm, across-position task differentiation based on US job posting data from Burning Glass Technologies (BGT, now Lightcast). In contrast to their measure, our measure is tailored towards measuring job requirements overlap between and within occupations. Another closely related paper is Djumalieva et al. (2018) who apply semi-supervised machine learning techniques to classify occupations based on skill requirements provided in online job ads in the UK collected by BGT.

[5] Examples include Cortes & Gallipoli (2018), Alabdulkareem et al. (2018), Belot et al. (2019), Belot et al. (2022), Lyshol (2022), Macaluso (2023), and Goos et al. (2019). Similarly, Gathmann & Schönberg (2010) measure occupational similarity based on data from the German Qualification and Career Survey and Eggenberger & Backes-Gellner (2023) and Eggenberger & Backes-Gellner (2023) utilize a measure for the specificity of a worker's human capital investment based on the skill bundles as specified in occupational training curricula in Switzerland. A further alternative, used in several recent studies on occupational mobility, is to build a measure of occupational similarity based on observed transitions between occupations (e.g., del Rio-Chanona et al., 2021; Schubert et al., 2024; Schmutte, 2014; Altmann et al., 2022). This approach is not appropriate for our project since transitions across occupations are our outcome of interest

& Wolthoff, 2020), suggests that job requirements are far from identical across jobs in the same occupation. The extent to which job requirements overlap within an occupation also depends on the granularity of the occupational classification. By providing an estimate of the within-occupation similarity of job requirements, we can, for example, examine whether job seekers and recruiters behave differently when an occupation is homogeneous or heterogeneous in its requirements.

One potential disadvantage of our approach, as compared to using task and skills dictionaries, is that employers may not list all job requirements in a job advertisement. For instance, an employer may require a specific educational qualification, which may also imply that they expect the skills that graduates with such a degree typically possess, and our measure of the overlap in job requirements could be biased. However, note that approaches to measure task and skills overlap using dictionaries may also be affected by measurement error, e.g. these dictionaries may not contain the most up-to-date information, or the information may be inaccurate. Measurement error likely affects all approaches to quantifying occupational similarity. We discuss measurement error below by showing how search patterns vary for occupations with closed (due to occupational licensing) vs open occupations.

2.2 Vacancy Data

We measure the overlap in job requirements using data covering the near-universe of online job postings in Switzerland between 2016 and 2022. This data, first used by Colella (2022) to analyze the impact of trade on labor demand, is collected by the private company x28 AG. The company continuously crawls job postings from all major online job boards and company websites in Switzerland, identifies duplicates, and assigns postings to industry and occupational classifications (Bannert et al., 2022). In total, the data covers at least 90% of all online job postings in Switzerland (Bannert et al., 2022). Bannert et al. (2022) show that the industry and regional composition of the x28 data is similar to that of the official statistics on company vacancies.

A key feature of the data—and one it shares with similar vacancy datasets in other countries—is that it comes with a list of job requirements extracted from the text and job title of each ad. x28 extracts these requirements by matching the text to keywords from a large, manually and continuously maintained database of terms related to the task and skill requirements of jobs. The granular ontology distinguishes between 2,775 different skills or tasks. It includes both soft and hard skills. Examples of job requirements include “accuracy”, “commercial understanding”, “sales skills”, “team orientation”, or various IT skills (e.g., knowledge of Python or SAP).

2.3 Approach

We measure the overlap in job requirements between two occupations in two steps. First, we randomly select pairs of vacancy postings for each of the occupation pairs that we compare. We then calculate the overlap in job requirements for the pair based on their Jaccard similarity: the number of job requirements mentioned by both vacancies relative to the total number of distinct job requirements mentioned in both job vacancies.

Figure A.1 shows a stylized example for an office clerk and shop sales assistant position. The two vacancies list a total of seven distinct job requirements: accuracy, business payment solutions, commercial understanding, communication, team orientation, appearance, and sales. Two of these job requirements are mentioned in both job vacancies: accuracy and team orientation. Thus, the Jaccard similarity of the two vacancies—the ratio between the common requirements relative to the seven distinct requirements—is $\frac{2}{7}$.

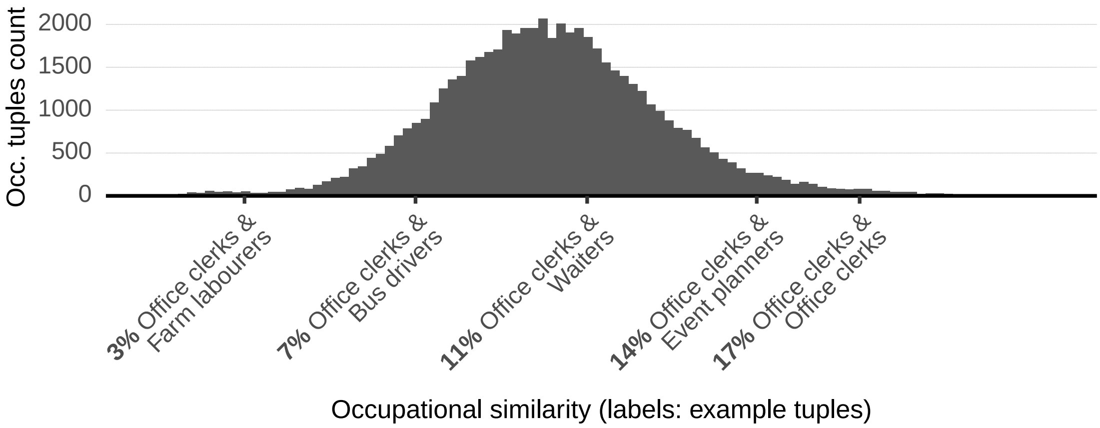
The second step in the construction of our overlap measure is to repeat step 1 for 5000 randomly drawn vacancy pairs[6] and then average the estimated Jaccard similarities over the randomly drawn pairs of job vacancies. We consider occupations with at least 200 posted vacancies between 2016 and mid-2022. Our sample covers 80% of all possible ISCO four-digit tuples (95% if we weight them by the number of ad views by job seekers). Intuitively, the measure captures the average overlap in the job requirements of two occupations. A distinct advantage of this procedure is that we can calculate the similarity within an occupation, too, as we can simply compute the Jaccard similarity for 5000 randomly drawn vacancy pairs from the same occupation.

2.4 Job Requirements Within and Across Occupation

Figure 1 shows the distribution of job requirement overlap across all occupation pairs. Here and throughout the paper, we classify occupations according to the fourth digit of the International Standard Classification of Occupations (ISCO 08). On the x axis, we illustrate the similarity index of office clerks to five other occupations. As expected, jobs for office clerks are most similar to other jobs that advertise for office clerks. Two randomly drawn vacancies within this occupation share on average 17% of their job requirements. On the other extreme, office clerks and farm laborers are quite distinct. On average, they have only 3% of job requirements in common. Finally, office clerks positions are quite similar to event planner positions. The average overlap in job requirements is around 14% for these two occupations. Focusing on the distribution across all occupation pairs,

[6] To do so we sample one vacancy from occupation A (with replacement) and one from occupation B (with replacement) and repeat this step 5000 times.

Figure 1: 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.

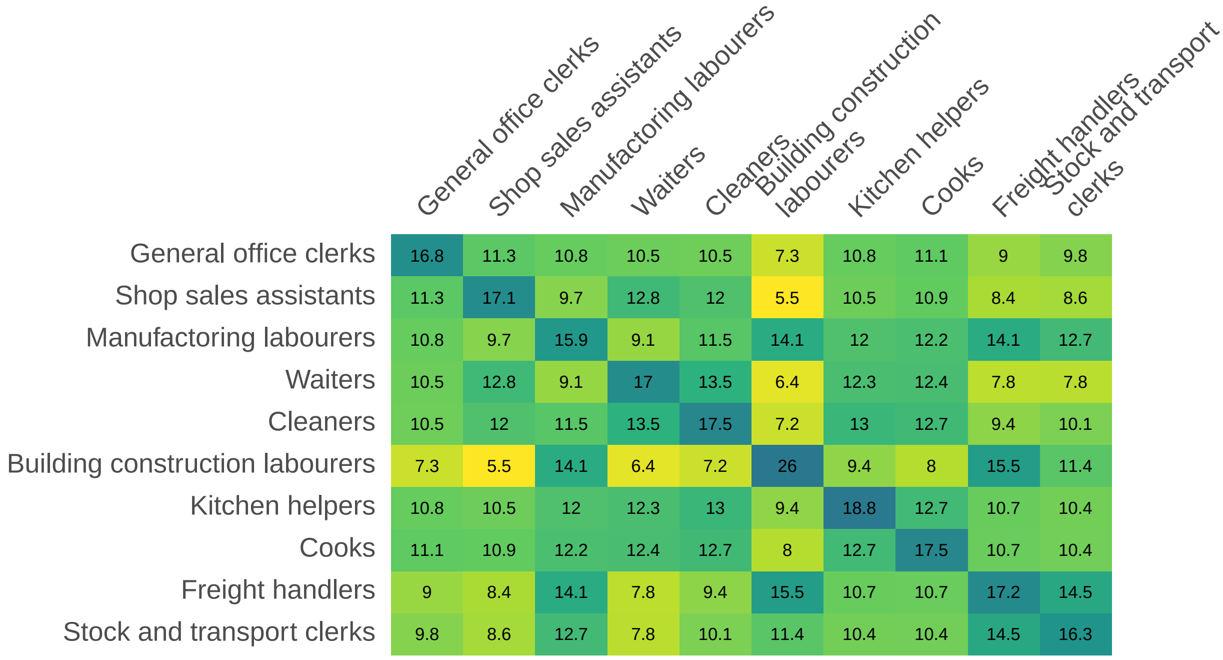
we find that the average overlap in job requirements between two distinct occupations is 10%. The within-occupation overlap is 17% on average. However, the similarity of job ads within an occupation varies substantially. It is as low as 12.7% for call center agents and as high as 42.5% for mixed crop and livestock farm laborers.

Figure 2 shows a matrix of similarity between the ten occupations with the largest number of job seekers according to the Swiss unemployment register. The matrix is symmetric, which reflects the fact that our similarity measure is symmetric. The color coding highlights the overlap in job requirements. It ranges from yellow (little overlap) to dark blue (high overlap). The fact that the diagonal is colored in blue shows that job ads posted in the same occupation tend to be relatively similar to each other. For instance, vacancies for building and construction laborers on average share 26% of their job requirements. In contrast, pairs of job vacancies for manufacturing laborers only share 15.9% of the job requirements, suggesting that this occupation is less homogeneous than building and construction laborers. The off-diagonal cells show the similarity between distinct occupations. For instance, vacancies for building construction laborers are most similar to freight handlers (15.5%), and least similar to job ads inviting applications from shop sales assistants (similarity: 5.5%) and waiters (6.4%). Manufacturing laborers need to satisfy similar requirements as freight handlers (similarity: 14.1%).

3 Data

This section documents the combination of click and register data from jobseekers and recruiters that we use for our empirical analyses.

Figure 2: Similarity between and within the ten occupations with the largest number of job seekers



Notes: This figure presents a similarity matrix of the job requirement overlap between and within the 10 occupations with most registered job seekers.

3.1 Data on job seekers' occupational search scope

Our analyses of job seekers' search across occupational boundaries draw from rich click and administrative data from the Swiss unemployment register.

The data have three features that facilitate analyzing job seekers' occupational scope. First, the data record the occupation of job seekers' last job before becoming unemployed as well as the occupation in which they found a job (if they exit unemployment with a job). We can thus analyze the realized occupational transitions.

Second, the data list all occupations that job seekers consider to work in. This list, which also determines what recruiters see when using the recruitment platform, is defined in the first bilateral meeting between the case worker of the public employment services (PES) and the job seeker. In this meeting, the case worker and the job seeker create a personalized job search profile that is binding: in principle, job seekers can be forced to apply to vacancies in the listed occupations, and may face sanctions if they fail to apply to a sufficient number of open positions in the listed occupations.

Finally, the register data can be linked to job seekers' online search activities if they use the job platform of the Swiss PES.[7] This job platform is "Job-Room.ch". The click data from the platform

[7] Bassier et al. (2023) use the data to study monopsony power of firms and Kopp (2022) uses the data to measure job-seekers preferences for part-time jobs. Klaeui (2024) combines the data with the X28 data on job openings to investigate the interplay between job seekers' consideration scopes and job finding from new openings.

Table 1: Descriptive statistics: Job seeker click data

	Sample (N = 77 843)				All spells (N = 295 908)			
	Mean	Median	Min	Max	Mean	Median	Min	Max
Female	0.5	1	0	1	0.46	0	0	1
Age (at registration)	38.87	37.44	15.43	64.68	38.1	36.42	1.29	71.04
Primary education	0.18	0	0	1	0.26	0	0	1
Secondary or vocational educ.	0.54	1	0	1	0.49	0	0	1
University education	0.22	0	0	1	0.16	0	0	1
Non-permanent resident	0.19	0	0	1	0.23	0	0	1
> 3 years tenure in last job	0.67	1	0	1	0.63	1	0	1
Insured earnings (CHF)	4594.93	4442	0	12350	3901.96	3991	0	12350
Spell duration (months)	6.76	5.67	0.03	23.5	5.32	4.07	0.03	23.5
N occupations (4-digits) in unemp. record search profile	2.24	2	1	14	2.18	2	1	14
N clicks	43.37	13	1	4521				
N days with at least one click	8.81	3	1	274				
Share of clicks in last occupation (4-digits)	0.31	0.12	0	1				
Distinct occupations clicked (4-digit)	9.36	4	1	223				
Distinct occupations clicked (3-digit)	7.94	4	1	102				
Distinct occupations clicked (2-digit)	6.15	4	1	40				
Distinct occupations clicked (1-digit)	3.4	3	1	10				
Share who find a job within 6 months	0.33	0	0	1	0.35	0	0	1
Conditonal share who find job in last occ. (4-digits)	0.48	0	0	1	0.5	1	0	1

Notes: Descriptive statistics on the characteristics of the job seekers in our sample. The sample is compared to the characteristics of the population of registered job seekers whose spells start within the period in which clicks on Job Room are recorded (06-06-2020 - 30-06-2021)

cover the one-year period between June 2020 and June 2021. The sample covers all registered job seekers who use the Job-Room to search for jobs and who view at least one vacancy on Job-Room. To be more precise, a view is when a job seeker has clicked on a vacancy that appeared in a result list after conducting a search on Job-Room. Appendix Figure A.3 shows a screenshot of the search mask and the result list on the job platform. We can attribute the clicks to register-based and verified information on the occupation of each vacancy. These click data allow us to track job seekers' occupational scopes at different points during their unemployment spell, and allow us to analyze whether the scope changes when labor market conditions change. We obtain the occupation (and further the location) of the clicked job postings from the API of job-room.ch that provides job posting details, including a list of occupations for every job ad. We use a cross-walk provided by the PES to translate between the internal occupational definition used in the API and the ISCO. A job listing may correspond to multiple internal occupations. Nonetheless, merely 3% of these listings align with more than one ISCO occupation at the most detailed level, and none are linked to more than three distinct ISCO codes. In those instances, we select an occupation at random from those matched to make the estimation process simpler by ensuring each job has a singular associated occupation.

We validate the use of Job-Room clicks as our primary measure of job seekers' occupational scope in Appendix Table A.1. The table shows that clicks on Job-Room are an extremely good predictor of the actual occupational transitions of unemployed job seekers. The table reveals a high positive correlation between a job seeker's share of clicks targeting her last occupation on Job-Room and the probability that this job seeker finds a job in the same occupation as the last job. This holds even if we control for a rich set of job-seeker characteristics and if we only compare job seekers that last worked in the same occupation, registered at the same point in time, and had the same initial regional search scope.

We impose a small number of sample restrictions. We remove data from job seekers with missing information on some key variables in the unemployment register[8], those that likely represent temporary lay-offs[9], and very few job seekers with a last occupation with an insufficient number of vacancies to compute our occupational distance measure.[10] Moreover, we drop 9% job seekers for whom we can not compute the number of vacancies for the tightness measure using X28 data. These cases most likely stem from differences between the two datasets in the granular ISCO-08 four digit occupations employed. The final sample consists of 77'843 job seekers.

Table 1 provides several key descriptive statistics for our sample of job seekers and compares them with all job seekers registered between June 2020 to June 2021. The table shows that the unemployment spell of Job-Room users lasted on average 6.8 months. They viewed on average 42 different vacancies on the platform during this period and returned to the platform relatively often: the average number of days on which we record at least one click per job seeker is 8.7. Moreover, many of the job seekers search across occupational boundaries: the average job seeker distributes her clicks to vacancies with 9 different ISCO four-digit codes and 3.4 different ISCO one-digit codes.

However, the last occupation nevertheless plays a predominant role among the occupations they consider. 31% of all job ads viewed are in the same four-digit occupation as their pre-unemployment job. Appendix Figure A.2 documents a substantial heterogeneity in the share of job seekers' clicks that target vacancies in their last occupation. The important role of job seekers' last occupation is even more visible in the actual (realized) transitions: conditional on finding a job within 6 months, 48% of all Job-Room users and 50% of all registered job seekers eventually find a job in their last occupation.

The comparison of the Job-Room user sample with the universe of registered unemployed in Table 1 reveals that 27.6% of all registered job seekers use Job-Room for job search in our sample

[8]We remove entries with missing data on insured earnings, region of residence, or stated search scope and with miscoded spell start or end dates.

[9]We exclude these job seekers because they may not be seriously looking for a new job given their high probability of recall to their last employer after the seasonal low. To exclude such cases, we remove unemployment spells of job seekers that eventually returned to the company they last worked at.

[10]We compute the index of job requirement overlap only for occupations with at least 200 vacancies in our near-universe vacancy database.

period. We also note some differences between job seekers who use the platform and those who do not. Women, older workers, and more highly educated workers, for instance, are somewhat more likely to use the platform. In addition, job seekers who use the platform had slightly higher earnings prior to unemployment and have somewhat longer unemployment spells. Due to these differences, we will verify whether our key job-seeker results are robust to using the data on the occupational search profiles defined in the first case worker meeting. This data is observed for all job seekers.

3.2 Data on recruiters' occupational search scope

A core innovation of this work is the use of online trace data of recruiters to study their search activities across occupational boundaries. As for the job seekers, we leverage data from the platform "Job-Room.ch", which is the job platform of the Swiss public employment service (PES). Job-Room allows recruiters to look up standardized CVs (profiles) of potential employees. The candidate profiles visible on the platform stem from job seekers registered at the Swiss Public Employment Service. 79% of the workers visible on the platform draw unemployment benefits. The click data that we use for this study were collected between March and December 2017.

Recruiters that use the platform typically start by entering the occupation of their open position. Oftentimes, they also specify the job's location. After entering the search criteria, recruiters get a result list with at most 100 candidates who exactly match the criteria. The result list contains a limited amount of baseline information about the respective job seekers.[11] If recruiters are interested in particular candidates on the result list, they can select them to see their full profile.

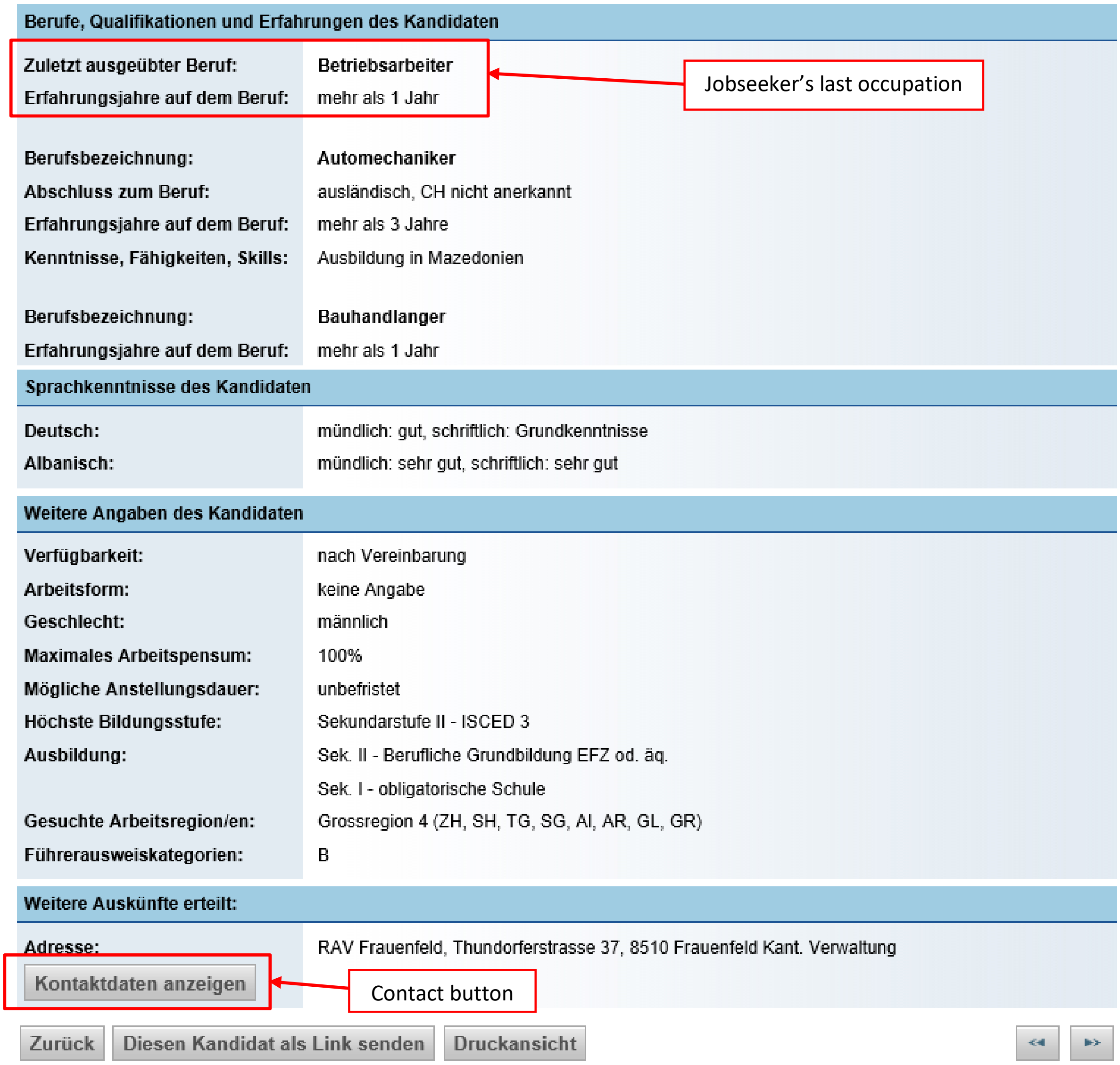
Figure 3 provides a screenshot of the full profile. Similar to a standard CV, the profile shows detailed information on candidates' skills and credentials, including their language skills, work experience, educational attainment, as well as personal characteristics such as gender, name, and nationality.[12] Importantly, the top of the candidate profile shows the occupation in which a candidate worked before he or she became unemployed. Just below the last occupation, recruiters also get information on all other occupations in which the job seeker is willing to work. For each occupation, recruiters see job seekers' years of work experience (in categorical format), the origin of the occupation-specific education certificate, and their skills and qualifications in the occupation. As explained in the previous section, the set of occupations listed on the candidate profile

[11] The result list shows candidates' desired work volume (in full-time equivalents), their gender, canton of residency, whether they are "immediately available" to start work, and certain skills and qualifications. Note that this preview does not show the job seeker's occupational labor market history.

[12] Hangartner et al. (2021) use this data to analyze gender and ethnic discrimination on the platform and provide an in-depth discussion of the data and its pros and cons.

is defined in the first bilateral meeting between the case worker of the PES and the registered job seeker. In this meeting, case workers are also encouraged to manually enter the job seekers' skills and qualifications that show up on the full profile view below each occupation.[13]

Figure 3: Screenshot of Candidate Profile on Job-Room



Notes: The figure shows a screenshot of the full candidate profile on Job-Room as seen by a recruiter.

If recruiters are interested in a candidate, they can access the contact details of the candidate by clicking on the "Show contact details" button. In 2017, it was not possible to contact and eventually hire candidates on Job-Room without clicking on this button. Hangartner et al. (2021) show that contact clicks increase the exit rate out of unemployment, suggesting that recruiters' contact attempts sometimes lead to hiring. Below, we use recruiters' contact clicks as our main

[13]As some case workers do not fill out the skill field in some or all occupations, the field "additional skills and qualifications" may not be shown for all occupations (as in Figure 3).

Table 2: Descriptive statistics on recruiter clicks.

	All observations	Last occ.= searched occ.	Last occ. $\neq$ searched occ
N recruiters	35 471		
N searches	381 194		
N distinct job seekers in result lists	281 190		
Mean N occupations listed per job seeker	2.4	0.95	1.45
Avg candidates in result list per search	37.8	19.8	17.9
Avg candidate views per search	9	5.1	3.9
Avg candidate contacts per search	4.1	2.5	1.6
Contact button click probability (%) (cond. on in result list)	21.34	22.47	17.55
Contact button click probability (%) (cond. on viewed)	45.83	48.73	42.56

Notes: The table reports descriptive statistics on the click behaviour of recruiters on Job-Room between March and December 2017.

dependent variable.

We restrict our sample to recruiter searches where an occupation was specified (98.3% of searches). We further restrict the sample to search-candidate pairs where we can compute the similarity measure for the overlap between the searched occupation and the candidate's last occupation. The similarity measure is computed for all occupations with at least 200 vacancy postings in the x28 data between 2016 and 2022.

Table 2 presents key descriptive statistics of the recruiter sample. During the sample period from March to December 2017, 33,216 recruiters conducted a total of 317,123 searches. The database of the platform contained 173,638 distinct job seekers. In terms of occupational coverage, Figure A.4 shows that a large share of recruiters search for craft and related trades workers, especially for construction workers, but that we observe a large number of searches in almost all occupational groups. On average, job seekers specify 2.4 occupations in which they are willing to work. For 95% of all job seekers, one of these occupations is the occupation they worked in before registering at the PES. As exemplified by the Screenshot in Figure 3, job seekers typically list occupations with prior work experience. Upon searching, recruiters see a result list of, on average, 38 candidate profiles, 20 of whom have last worked in the searched occupation. Recruiters attempt to contact 46% of the job seekers whose profiles they visit. The contact probability is substantially lower—21%—if we express it as a share of all job seekers in the result list.

Finally, an important question is how often recruiters view and contact job seekers who last worked in a different occupation than the one in which they are looking for candidates. Table 2 shows that 57% of the viewed profiles belong to job seekers whose last job was in the recruiters' searched occupation. Appendix Figure A.5 shows the share of contacted job seekers with a last job in the same occupation as recruiters' searched occupation. On average, this share is 60%, but it varies substantially across recruiters. These numbers imply that recruiters often encounter job seekers who last worked in a different occupation and would now like to switch.[14]

4 The role of overlap in job requirements

We are interested whether job requirement overlap is relevant in determining search across occupational boundaries on both market sides. This analysis also validates our measure of occupational distance, as the measure turns out to be highly predictive of the online search behavior of both jobseekers and recruiters.

4.1 Jobseekers' search scope and overlap

We start by relating job seekers' occupational search scope, as measured in the click and register data, to the index of job requirement overlap. As a first step, we use a highly granular dataset with a separate observation for each job seeker, month, and occupation combination. Our data contains information on 238 distinct four digit ISCO occupations. We then simply count the number of clicks each job seeker makes in every occupation-month cell.

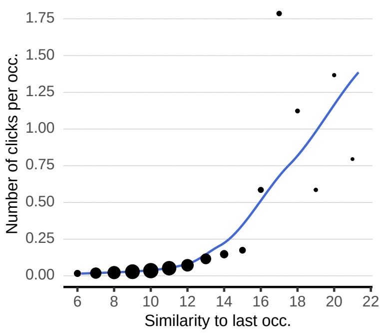
Using this dataset, Figure 4, panel a), shows a binned scatter plot of the number of clicks per occupation[15] against the overlap in job requirements between the occupation of the clicked vacancy and the occupation in which the job seeker worked before becoming unemployed. The figure also shows a fitted regression line from a local linear regression. Job seekers rarely click on job ads in occupations that have less than 11% overlap in job requirements to their last occupation. Conversely, we observe approximately one click per month on ads in occupations where the overlap is 19%. This evidence suggests that overlap in job requirements plays a key role in explaining how job seekers allocate clicks across occupations.

Panel (b) of Figure 4 shows the same relationship as panel (a) but restricts the sample to clicks in job seekers' last occupations. The figure shows, first, that job seekers click on job openings in their last occupation much more frequently than on vacancies from any other occupation. Second, job seekers view fewer job ads in the last occupation per month if the occupation is there is a lot of heterogeneity within this occupation in terms of job requirements. Conversely, job seekers search more actively in their last occupation if job ads in this occupation have high overlap in requirements. This evidence suggests that overlap in job requirements is predictive of job seekers'

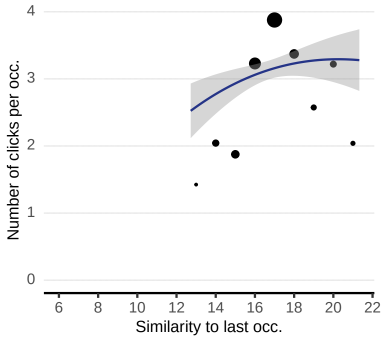
[14]The second Panel of Appendix Figure A.5 shows the average similarity of the last occupation of a job-seeker to the occupation of the vacancy. The distribution is centered around the mean of a similarity score of 17. There are apparently quite some recruiters who also consider job-seekers from occupations with a modest overlap in job requirements.

[15]We winsorize the number of clicks per cell at the 99th percentile (25 click per month).

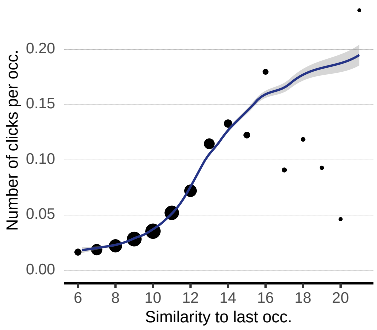
Figure 4: Job seeker's occupational search scope and the overlap in job requirements between occupations



(a) All occupations



(b) Clicks in the last occupation



(c) Clicks outside of the last occupation

Notes: The figures show binned scatter plots of the number of vacancy clicks in an occupation against our measure of overlap in job requirements between the occupation of the vacancy and the occupation in which a job seeker worked last. Clicks are measured at the job seeker-occupation-month-level. The size of the dots is proportional to the number of job seeker-month-occupation observations. The similarity score is truncated at the 5th and 95th percentile of observations. The number of clicks is windsorized at p99 (25 clicks per occupation, month and job seeker). The lines represent local linear regressions. The average number of clicks is 0.006. Panel (a) is based on a sample with all occupations, panel (b) only looks at clicks within the last occupation of a job seeker, the variation comes from different job seekers having different last occupations with varying within-occupation similarities, and panel (c) reports the relationship for vacancy clicks where the job seeker's last occupation differs from the occupation of the vacancy.

clicks even within job seekers' last occupation.

Figure 4, panel (c), focuses on clicks on vacancies in all occupations, excluding vacancies requesting the same occupation that the job-seeker has worked previously. Job seekers are more likely to click on vacancies in occupations that overlap more strongly with their previous occupation, even excluding those occupations that job seekers have worked in before. The figure shows that the relationship in panel (a) is not solely driven by clicks to the last occupation.

Table 3 provides linear regressions of the relationship between the overlap in job requirements and job seekers' number of clicks in an occupation. An advantage of these regressions is that we can control for job seeker fixed effects and a job seekers labor market history. By focusing solely on the occupational choices of the same job seeker, we implicitly control for unobserved factors correlated with both, a job seekers' clicks and her last occupation. For instance, we account for job seekers' overall search intensity and whether the job seeker has already worked in an occupation in the more distant past, prior to the last occupation.

Column 1 of Table 3 uses the data from Figure 4, panel a) and confirms the strong predictive power of occupational similarity and a job seeker's last occupation for the number of clicks per occupation even when we condition on job seeker fixed effects.[16] Both estimates are large in size.

[16]This regression setup is very similar to the estimation in Marinescu & Rathelot (2018). They look at counts of applications sent by job seekers to jobs in different geographic units and investigate the role of distance. We look at

Table 3: Job seeker's occupational search scope and the overlap in job requirements between occupations

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	N clicked	N clicked	N clicked	In search profile	In search profile
Similarity	0.2723*** (0.0033)	0.1885*** (0.0024)		0.0018*** (1.05e-5)	0.0017*** (5.35e-6)
Occupation = Last occupation	2.554*** (0.0219)		0.7669*** (0.0175)	0.9377*** (0.0008)	0.9352*** (0.0004)
Difference in log median wage		-1.302*** (0.0201)	-1.378*** (0.0195)		
Prior experience in occupation = >3years		3.326*** (0.0166)	3.743*** (0.0178)		
Prior experience in occupation = 1-3years		2.944*** (0.0240)	3.361*** (0.0229)		
Prior experience in occupation = <1year		2.882*** (0.0346)	3.275*** (0.0301)		
Job seeker spell FE	Yes	Yes	Yes	Yes	Yes
Family	Poisson	Poisson	Poisson	OLS	OLS
Observations	17,102,107	17,102,107	17,102,107	22,381,683	83,320,575
Mean of dependent var.	0.18344	0.18344	0.18344	0.00517	0.00505
Pseudo R2 / R2	0.4256	0.4991	0.4825	0.4228	0.4339
Number of spells	76,913	76,913	76,913	76,913	295,908

Notes: Estimates whether a job seeker searches in an occupation on the overlap in job requirements between the occupation and the job seeker's last occupation before unemployment. Columns (1) - (3) show Poisson regression estimates, the outcome is the number of clicks on job-room.ch aggregated over the unemplyoment spell. One observation is a job seeker spell - occupation combination. Columns (4) - (5) show estimates from a linear probability model, the outcome is whether job seekers reports that they are willing to take up work in the occupation. This information is determined in the first meeting with the case worker upon registering as unemployed. One observation is a job seeker-occupation combination. Column (4) looks at the sample of job-room.ch users, as do Columns (1) - (3). The sample in Column (5) includes all registered job seekers starting their spell between June 2020 and June 2021. The wage difference is computed as the log median wage in the occupation minus the log median wage in the job seeker's last occupation. Standard errors are clustered at the unemployment spell level.

Job seekers click on job ads in their last occupation 13 times (= $exp(2.554)$) more often than on job ads in other occupations with comparable job requirement overlap. Similarly, an occupation that has a 20% overlap in job requirements to a job seeker's last occupation receives 15 times more clicks than an occupation with an overlap of 10%.

Columns 2 and 3 of Table 3 provide regressions where we additionally control for the log wage gap between a job seeker's last occupation and the occupation of the vacancy[17] as well as for job seekers' professional experience in each occupation. The two columns show that similarity predicts job seekers' clicks even if we account for prior professional experience and the log wage differentials.[18] The relevance of similarity and the last occupation for job seekers' search is thus not solely explained by the fact that job seekers, by definition, possess work experience in their last occupation and likely have work experience in occupations with similar job requirements, too.

Finally, columns 4 and 5 provide estimates of linear probability models that, instead of using actual clicks as dependent variable, use a dummy equal to one if a particular occupation appears in

click data and occupational similarity.

[17]We use median wages per ISCO 4-digit occupation as computed by merging the 2017–2019 waves of the Swiss Structural Surveys, which contain detailed occupation codes, to the 2018 wave of the Swiss earnings structure surveys, which contain highly reliable employer-reported hourly wages for a large number of Swiss workers.

[18]The regressions uncover a negative relationship between clicks and the log wage differential between job seekers' last occupation and the targeted occupation. These results are consistent with the existing literature that documents that occupational mobility is, in certain cases, such as for low-wage earners, associated with downward moves along the occupational wage ladder (e.g., Bachmann et al., 2020; Groes et al., 2015; Altmann et al., 2023).

the job seekers' occupational search profile defined in the first meeting with the case worker of the PES. The results confirm that job requirements overlap and job seekers' last occupation determines job seekers' occupational scope. Moreover, the estimated coefficients on the main variables are very similar if we run this regression only for job seekers that use the Job-Room (column 4) and for all job seekers registered with the PES between June 2020 and June 2021 (column 5), suggesting that the findings based on clicks of Job-Room users may be representative for the entire sample of registered job seekers.

4.2 Recruiters' search scope and overlap

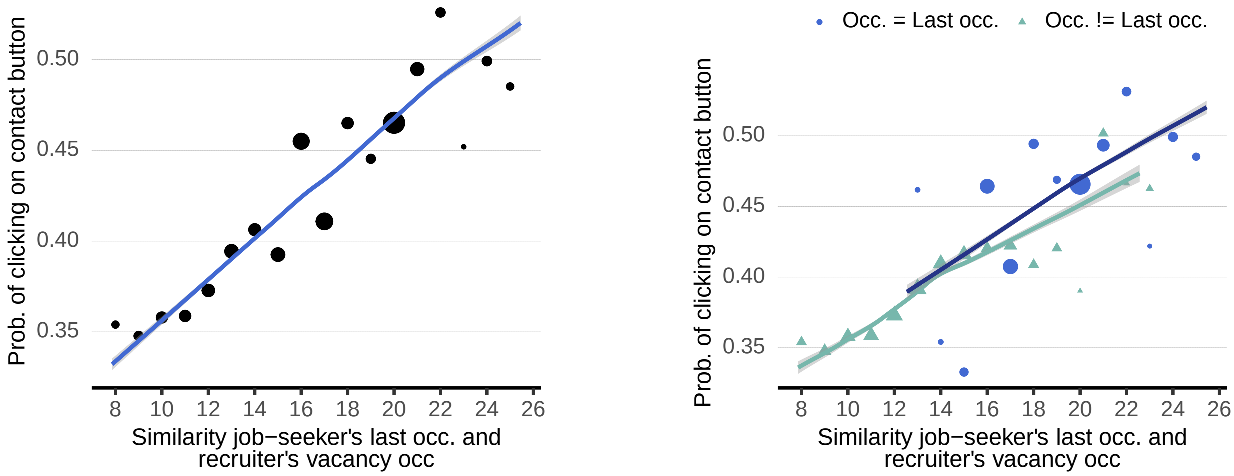
The previous section has demonstrated that job requirement overlap strongly predicts the occupations that registered job seekers target when searching for jobs on Job-Room. In this section we look at the labor demand side. How does the likelihood that recruiters contact job seekers depend on the job seekers' last occupation and the similarity of that occupation with recruiters' searched occupation in terms of overlap in job requirements? To answer these questions, we now analyze the determinants of recruiters' contact probabilities on the recruitment platform of Job-Room.

Figure 5a, panel a), shows the bivariate relationship between the contact rate—the probability that recruiters click on the contact button conditional on seeing a candidate profile (see Figure 3)[19]—and the overlap in job requirements between recruiters' searched occupation and the occupation in which the job seeker worked last. Recall that the search list of recruiters is composed of job seekers who stated in their case worker meeting that they are willing to work in the occupation the recruiter seeks to fill. Frequently, these job seekers have already worked in the occupation. Despite this pre-selection, we observe a strong positive relationship: The average contact rate ranges from 35% if the overlap in job requirements is very small to 50% if the overlap is very large. This suggests that overlap between a job seekers last occupation and the searched occupation is relevant, even though most job seekers who end up in recruiters' search lists have prior professional experience in recruiters' searched occupation.

Panel (b) of Figure 5 differentiates between job seekers who worked in recruiters' searched occupation prior to becoming unemployed and job seekers who worked in a different occupation. It shows that there is a positive relationship between the overlap in job requirements and recruiters' contact rate both across and within occupations. The contact rate, for instance, is substantially higher for candidates that last worked in a different occupation with high overlap. Moreover, re-

[19]Note that recruiters do not see any information about the types of occupations and the experience in these occupations, the occupational background, of a candidate before viewing the profile.

Figure 5: Recruiters' contact rate and the overlap in job requirements between recruiters' searched occupation and candidates' last occupation



(a) All seen candidates

(b) By candidates last occupation

Notes: The figures show binned scatter plots of the probability of clicking on the contact button conditional on visiting the profile of a job-seeker against our measure of overlap in job requirements between the occupation of the vacancy and the occupation in which a job-seeker worked last. The similarity score is truncated at the 5th and 95th percentile of observations. The lines represent local linear regressions. The average contact click probability is 0.43. While panel (a) is based on the whole sample, panel (b) reports the relationship for two separate sub-samples: Profile visits where the job-seeker's last occupation corresponds to the occupation of the vacancy and profile visits where the job-seeker's last occupation differs from the occupation of the vacancy.

cruiters in occupations with heterogeneous job requirements are more flexible regarding job seekers' last occupation, possibly because having a last job in the occupation is no guarantee that the job seeker meets the job requirements.

A potential concern with the descriptive evidence in Figure 5 is that job seekers who last worked in a recruiter's searched occupation or a very similar occupation may also be better candidates in other respects than those who have last worked in a distant occupation. We address this concern through the way recruiters contact job seekers. The information that is available to recruiters when deciding on whether to contact a job seeker is also available to us. We therefore can address selection through controlling for observables in our setting to isolate the causal effects of job requirement overlap and candidates' last occupation on recruiters' contact decisions. Following Hangartner et al. (2021), we estimate linear probability models of the contact rate on job seekers' occupational background while holding constant all other job-seeker characteristics that influence recruiter decisions on Job-Room. We estimate variants of the following model:

$$y_{i,s} = \alpha I[l(i) = o(s)] + \beta similarity_{l(i),o(s)} + \delta exp_{i,o(s)} + \lambda edu_{i,o(s)} + \gamma_i + \phi_s + \psi_{rank(i,s)} + \varepsilon_{i,s} \quad (1)$$

The dependent variable, $y_{i,s}$, is the probability that the recruiter clicks on the contact button when screening job seeker i's full profile. The first key explanatory variable is $I[l(i) = o(s)]$, which is an indicator variable equal to one if candidate i's last occupation, $l(i)$, matches recruiter's target occupation in search s, $o(s)$. The second key variable is $similarity_{l(i),o(s)}$, which measures the overlap in job requirements between recruiter's searched occupation and a candidate's last occupation. We control for $exp_{i,o(s)}$, which represents a vector of controls for candidate i's prior professional experience in the searched occupation $o(s)$, and $edu_{i,o(s)}$, which account for candidate i's educational certificates in the searched occupation $o(s)$. We also control for a series of rank fixed effects, $\psi_{rank(i,s)}$, that control flexibly for the absolute rank and the relative rank of a job seeker within the list of search results.

The key ingredients in terms of causal identification in 1) are the search fixed effects, ϕ_s, and the candidate fixed effects, γ_i. The search fixed effects imply that we control for all recruiter-specific factors that could influence her search. The candidate fixed effects, in turn, control for all candidate characteristics that influence contact rates and are constant across searches of recruiters. Examples are job seekers' gender, nationality, or highest educational attainment. The reason why we can control for candidate fixed effects without absorbing the effects of interest is that the same job seeker appears in the result lists of recruiters searching in different occupations.[20]

Table 4 shows the results of several linear probability models of equation 1. The table provides at least two important insights. First, the likelihood that recruiters contact job seekers decreases as the job requirement overlap between a recruiter's searched occupation and a candidate's last occupation decreases. As columns 1 and 2 show, similarity predicts recruiter interest independent of whether we control for candidates' last occupation. To interpret the size of the effect in our preferred specification (column 3), it is instructive to compare two job seekers, one who last worked in an occupation with 20% overlap to recruiters' searched occupation and one who last worked in an occupation with only 10% overlap. The former is 2.3 percentage points (or 5.4% relative to the mean contact rate) more likely to be contacted holding everything else constant—including professional experience in recruiter's searched occupation. Benchmarking this effect against the benefits of having professional experience in an occupation suggests that a 10 percentage points higher overlap is equivalent to having approximately one year of work experience in an occupation. The similarity of the coefficients on the two interaction terms in column 4 shows that overlap influences the contact rate to the same extent among job seekers who last worked in recruiters'

[20] In one search, for instance, the job seeker may appear to a recruiter looking for someone in that job seeker's last occupation. In another search, the same job seeker may not have last worked in the recruiter's searched occupation but is willing to switch to it.

Table 4: Effect of occupational similarity on recruiters' contact decisions

	(1)	(2)	(3)	(4)
Dependent Var.:	Contact button clicked	Contact button clicked	Contact button clicked	Contact button clicked
Similarity	0.0060*** (0.0003)	0.0028*** (0.0004)	0.0023*** (0.0004)	
Last worked in different occ. x Similarity				0.0023*** (0.0004)
Last worked in searched occ. x Similarity				0.0024*** (0.0006)
Last worked in searched occ.		0.0228*** (0.0024)	0.0194*** (0.0024)	0.0170* (0.0088)
Prior experience in searched occ. = <1year			0.0121*** (0.0033)	0.0122*** (0.0033)
Prior experience in searched occ. = >3years			0.0525*** (0.0033)	0.0526*** (0.0034)
Prior experience in searched occ. = 1-3years			0.0326*** (0.0032)	0.0327*** (0.0032)
Swiss professional qualification in searched occ.			0.0276*** (0.0025)	0.0276*** (0.0025)
Foreign prof. qual. in searched occ. (Accepted in CH)			0.0230*** (0.0036)	0.0230*** (0.0036)
Foreign prof. qual. in searched occ. (not accepted in CH)			-0.0087** (0.0039)	-0.0087** (0.0039)
Recruiter search FE	Yes	Yes	Yes	Yes
Search rank	Yes	Yes	Yes	Yes
Search rank (relative)	Yes	Yes	Yes	Yes
Job seeker spell FE	Yes	Yes	Yes	Yes
--	----------------------	----------------------	----------------------	----------------------
Observations	2,826,810	2,826,810	2,826,810	2,826,810
R2	0.48557	0.48560	0.48586	0.48586
N searches	315,423	315,423	315,423	315,423
N recruiters	33,109	33,109	33,109	33,109
Baseline prob.	0.4300	0.4300	0.4300	0.4300

Notes: This table presents the results from a linear probability model analysis designed to investigate the impact of the similarity between a job seeker's last occupation and the occupation sought by recruiters on the likelihood of a recruiter clicking to reveal a job seeker's contact details. Each observation represents a job seeker profile that was opened by a recruiter following a search. The similarity index is derived from the overlap in job requirements between two average vacancies across occupations, calculated using data from job-room.ch and the similarity measure from X28. The occupational median wages are retrieved from the Swiss Earnings Structure Survey. The similarity measure is windsorized at the 5th percentile for observations where the last occupation differs from the searched occupation and at the 95th percentile for observations where they are the same. It is expressed in percentage units, an overlap of 10% of job requirements corresponds to a number of 10. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

searched occupation and those who last worked in a different occupation.

The second key insight from Table 4 concerns the role of job seekers' last occupation. Columns 2–4 show that job seekers' last occupation matters to recruiters even though most job seekers who appear to recruiters have prior professional experience in recruiters' searched occupation. In our preferred specification, job seekers who last worked in the recruiter's searched occupation have a 1.9 percentage points higher probability (or 4.5% relative to the mean contact rate) to be contacted than job seekers who did not. The effect is comparable to the effect of having one year of work experience compared to having no experience in recruiter's searched occupation.

Taking stock, we find that job requirements overlap and job seekers' last occupation are both important factors in explaining recruiters' and job seekers' search across occupational boundaries on Job-Room.

5 The role of labor market tightness

In imperfect labor markets, there often exist occupations that have relatively few jobs per worker while, at the same time, there exist occupations with relatively many jobs per worker. In such a situation it is efficiency-improving for workers to move from slack occupations to tighter occupations (Kircher, 2022). We are unaware of empirical analyses that directly analyze whether recruiters and job seekers indeed adapt their search to occupational imbalances.[21] In this section, we fill this gap by investigating the effect of tightness in an occupation on job seekers' willingness to change occupation and recruiters' willingness to consider candidates from other occupations.

5.1 Measuring Tightness

To understand whether recruiters and job seekers react to imbalances in supply and demand across occupations, we construct a time-varying, occupation, and region-specific measure of labor market tightness. To ensure that our measure is not mechanically related to users' search behavior on Job-Room, we do not use a platform-specific tightness measure but instead construct one based on external data. The two data sources used cover the universe of online job openings and registered job seekers.

For each occupation-region cell, we measure tightness as the 30-day moving average of the number of online vacancies divided by the number of unemployed job seekers around a given day. Formally,

$$tightness_{o,\mathcal{C},t} = \frac{V_{o,\mathcal{C},t}}{U_{o,\mathcal{C},t}} \tag{2}$$

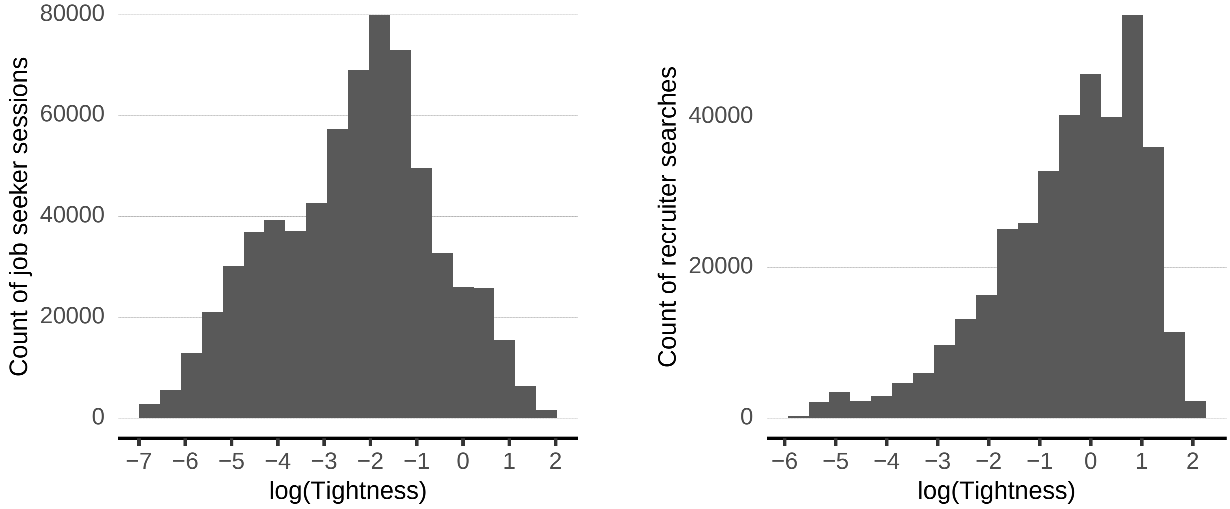
where $V_{o,\mathcal{C},t}$ represents the stock of online vacancies in occupation o and region $\mathcal{C}$ in the 30-day rolling average around day t. The data come from the private firm x28 and cover the near-universe of online vacancies posted on job boards and firm websites in Switzerland (see section 2.2 for a description).[22] Similarly, $U_{o,\mathcal{C},t}$ represents the average number of job seekers registered as unemployed in the 30 days around day t that last worked in occupation o and look for a job in region $\mathcal{C}$. These data stem from the Swiss unemployment register.

We assign the tightness measure to job seekers and recruiters in the following way. On the job-seeker side, occupation o represents her last occupation, d the day of the online search, and the region $\mathcal{C}$ reflects the combination of cantons in which she is willing to work as defined in the first meeting between the job seeker and the PES case worker. On the recruiter side, o represents recruiters' searched occupation, d the day of the search, and $\mathcal{C}$ is the canton (or one of 7 broader regions, each comprising a list of cantons) that 80% of recruiters specify when searching for a

[21] An exception is Altmann et al. (2023), who descriptively analyze how job seekers' search strategies correlate with labor market tightness

[22] The vacancy stock is computed as the difference between the inflows and outflows of vacancies. Inflows are identified by the publication date, while outflows correspond to the date when the vacancy was removed from the internet.

Figure 6: Distribution of the tightness measure



(a) Job seekers

(b) Recruiters

Notes: Panel (a) shows a histogram of the log tightness of job seekers' sub-markets. Panel (b) shows a histogram of the log tightness of recruiters' sub-markets.

candidate on Job-Room. For recruiters who do not restrict their search regionally, the search region is defined as Switzerland as a whole.[23]

Figure 6 shows the distributions of the logarithm of our tightness measure for job seekers (panel a) and recruiters (panel b). There is substantial variation in both measures, both cross-sectionally and over time. The tightness measure is lower on the job seeker side than on the recruiter side.[24]

5.2 The effect of tightness in job seekers' last occupation

We first examine the effect of tightness in a job seeker's last occupation on her occupational search scope. We measure a job seeker's occupational scope with a relatively narrow and with a more encompassing outcome variable: i) the probability that a job seeker clicks on a vacancy in an occupation that matches her last occupation, and ii) the overlap in job requirements between the occupation of the clicked vacancy and a job seeker's last occupation. The lower the average overlap, the broader is a job seeker's occupational scope.

Appendix Figure A.7 shows how tightness in a job seeker's last occupation correlates with these two measures of job seeker's occupational scope. It reveals a positive correlation for both measures:

[23] Recruiters also have the possibility to do a search across all occupations, however only 1.3% of searches do not use occupation as a filter criteria. We omit those searches from our sample.

[24] A plausible explanation is the different occupations in which recruiters and job seekers search and reflects one of the main sources of frictional unemployment: unemployed job seekers are more likely to come from occupations with a structurally lower demand—occupations with few vacancies per job seeker. Recruiters that engage in active recruiting, on the other hand, likely search in occupations with relatively few job seekers per vacant job.

job seekers whose last occupation becomes tighter are less likely to click on vacancies outside their last occupation (panel a), and they are more likely to click on vacancies that have a higher job requirements overlap with their last occupation (panel b).

To test more formally whether this positive relationship holds even if we control for observed and unobserved job-seeker characteristics, we estimate variants of the following regression model:

$$y_{it} = \beta log(tightness_{l(i),\mathcal{C}(i),t}) + \alpha_i + \phi_{\tau(i,t)} + \delta_{m(t)} + \varepsilon_{it} \tag{3}$$

We look at different dependent variables y_{it} measuring the occupational scope of a job seeker's search session. The first is the number of job postings a job seeker views in her last occupation. The second is the converse: The number of jobs clicked on outside of the job seeker's last occupation. Then we also look at a relative measure: the share of vacancies that job seeker i views in his last occupation on day t. Finally, we investigate the impact of tightness on the average similarity between the job seeker's last occupation and the occupation(s) of all vacancies viewed per day. The key explanatory variable is $log(tightness_{l(i),\mathcal{C}(i),t})$, the logarithm of the vacancy-to-unemployment ratio in a job seeker's last occupation and search region on day t. Our baseline specification includes a job seeker fixed effect α_i, which controls not only for differences in a job seeker's last occupation and her cantonal search scope, but also for all time-constant (un)observed characteristics of a job seeker. We also control for the elapsed unemployment spell duration $\phi_{\tau(i,t)}$, as spell duration is a potentially important time-varying confounder.[25] We also include calendar month fixed effects, $\delta_{m(t)}$. Thus, the effect of labor market tightness on a job seeker's occupational search scope is identified by comparing searches of the same job seeker looking for jobs at different points in time while holding spell duration constant.

The results of estimating equation 3 using Poisson (columns 1–3) and OLS (columns 4–5) are shown in Table 5. Columns 2–3 show that job seekers who last worked in an occupation that becomes tighter substantially increase the number of daily clicks on ads in their last occupation. At the same time, they decrease the number of clicks on ads in different occupations. The total number of ad views does not change significantly (column 1). As a consequence, an increase in the vacancy-to-unemployment ratio increases the share of clicks on ads in a job seekers' last occupations (column 4). Consistently, an increase in tightness also leads to an increase in the average similarity

[25] It is a priori plausible that unemployment spells are longer, the worse the labor market conditions in a job seeker's last occupation. At the same time, job seekers' occupational search scope may change, the longer the spell. However, as Figure A.9 in the Appendix shows based on the coefficient estimates from equation 3 that this does not seem to be the case. Job seekers' occupational search scope does not change significantly over the course of their unemployment spell.

Table 5: Effect of tightness in the last occupation on job seekers' occupational search scope

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	N clicked	N clicked same occ	N clicked diff. occ	Share clicked same occ.	Avg. similarity
log(Tightness)	-0.0003 (0.0098)	0.1019*** (0.0181)	-0.0246** (0.0109)	0.0154*** (0.0020)	0.0878*** (0.0146)
Elapsed spell duration FE	Yes	Yes	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes	Yes	Yes
Job seeker spell FE	Yes	Yes	Yes	Yes	Yes
Family	Poisson	Poisson	Poisson	OLS	OLS
Observations	672,109	553,307	655,604	672,109	672,109
Number of spells	77,843	50,283	69,456	77,843	77,843
Pseudo R2 / R2	0.3329	0.2990	0.3042	0.3845	0.7399
Mean of dependent var.	4.859	1.537	3.685	0.2964	13.06

Notes: Regression of job seeker vacancy click behavior on the tightness in the occupation of the job seeker's last occupation before unemployment. Estimates in Columns (1) - (3) are from a Poisson regression. Estimates in Columns (4)-(5) are from a linear regression. Every search session of a job seeker is one observation. A search session is defined as a day with at least one click. Standard errors are clustered at the unemployment spell level.

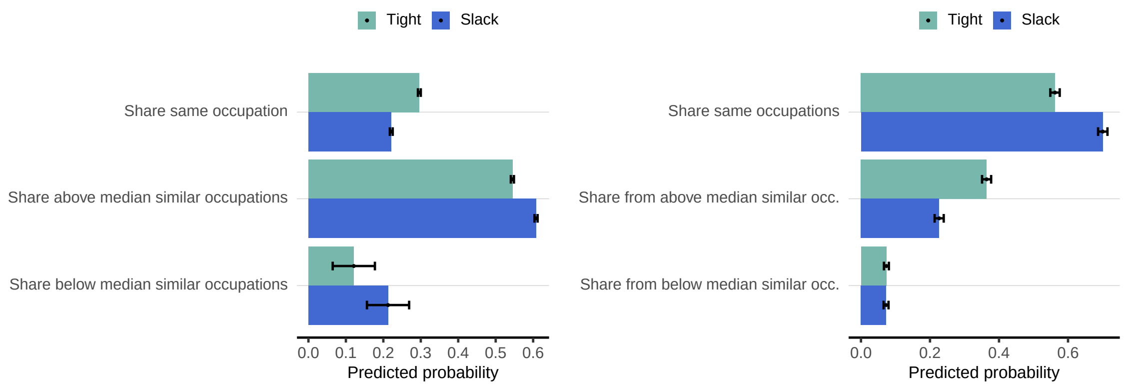
between the occupations of the clicked ads and job seekers' last occupations (column 5).

Figure 7, panel a, illustrates the magnitude of the effect of tightness on job seekers' occupational scope. It also shows which other occupations job seekers switch to when their last occupation becomes more slack. The first two bars in the figure use the regression estimate from column 4, Table 5, to predict the share of ad views in a job seeker's last occupation for tight (90th percentile of the tightness measure) and slack (10th percentile) occupational labor markets. The lower part of the subfigure analyzes which occupations job seekers look at if they click on ads in occupations different from their last. The outcome variables are the share of ad clicks in occupations with an above-median job requirement overlap and the share of clicks with a below-median overlap. The plot shows that job seekers from a tight occupation allocate 29.6% of their ad views to that occupation. If the occupation becomes slack, only 22.1% of their clicks are in their old occupation. Job seekers in slack occupations increase their clicks both in occupations with high job requirements overlap as well as in occupations with low overlap.

Appendix Table A.2 shows that the estimates of the effect of tightness in a job seeker's last occupation on her occupational scope are robust to different specifications. The estimated coefficient becomes somewhat smaller than in our baseline regression when we replace the job seeker fixed effect with an indicator for the last occupation interacted with a job seeker's regional search scope, but it remains highly significant (see column 1). Adding job seeker characteristics as additional controls does not change the coefficient significantly either (column 2). The tightness effect also does not change much when we control for the average distance of a job seeker to the location of the vacancy (column 4).[26]

[26] It is worth noting that this effect is significantly positive for both outcomes. This suggests a trade-off between

Figure 7: The impact of tightness on job seekers' and recruiters' search scope: Illustrating the magnitude



(a) Job-seeker clicks to open vacancy postings (b) Recruiter clicks to contact candidates

Notes: Effects on the predicted probability from our regression estimates. "Tight" indicates that the tightness is set at the 90th percentile of the tightness within the sample. "Slack" indicates the 10th percentile. The control variables are fixed at their mean effects. The job-seeker regressions in Subfigure (a) control for the calendar month of the click date, for the elapsed spell duration at click (measured in monthly dummies) and for a job seeker fixed effect. The recruiter regressions in Subfigure (b) control for the occupation and the canton of the vacancy the recruiter searched for, for the calendar month of the recruiter search and for a recruiter fixed effect.

We can also use the estimates of other determinants of the occupational scope in Appendix Table A.2 to benchmark the tightness effect. For instance, high experience in the last occupation creates a lock-in effect, as job seekers are less likely to click on ads from other occupations.[27] The effect of high experience in the last occupation (i.e. more than 3 years) is similar in magnitude to moving from a labor market in the 10th decile of the tightness distribution to a labor market in the 90th decile.

An interesting question is whether job seekers mainly adapt their search as a response to the number of vacancies—the numerator of the tightness measure—or to the number of job seekers—the denominator. Do they mainly react to the number of vacancies in an occupation, as this number is salient when conducting online searches? Or do they also respond to competition from other job seekers in the occupation, although this effect may be less salient? Appendix Table A.3 suggests that both channels play a role. While the effect of the number of vacancies is more precisely estimated and the effects are somewhat larger, the number of (other) job seekers searching in the same market also affects job seekers' search behaviors. The results suggest that, conditional on the number of job seekers, increases in the number of vacancies in the job seeker's last occupation

distance and similarity. Job seekers looking for jobs far away seem to require a compensation in the form of a higher similarity of these jobs.

[27]This is consistent with the results presented in Table 3, which shows that prior experience in an occupation significantly increases the number of ad views from that occupation. The estimates in column 2 also show that women, older job seekers, and more educated job seekers tend to have a narrower occupational search scope than men, younger job seekers, and those with a primary education.

increase clicks to job ads in that occupation, decrease clicks to job ads outside that occupation, and as a result, increase the share of clicks on the occupation with more vacancies. Reductions in the number of job seekers, holding constant the number of vacancies, reduce search activity of job seekers without significant effects on the targeting of search.

5.3 The effect of tightness in recruiters' searched occupation

We now turn to the recruiter side and assess whether they become more open to occupational switchers when the occupations in which they are seeking to fill vacancies become tighter. Appendix Figure A.8 shows the descriptive relationship between the labor market tightness in recruiter's searched occupation and his or her openness to occupational switchers. The figure reveals a clear negative correlation: recruiters who search in an occupation in times of high tightness are more open to job seekers coming from a different occupation. They are also more likely to contact job seekers that last worked in more distant occupations. To analyze whether this visual evidence is causal, we estimate the impact of the vacancy-to-unemployment ratio in recruiters' searched occupation on recruiters' occupational scope using the following regression model:

$$y_{rs} = \beta log(tightness_{o(s),\mathcal{C}(s),t(s)}) + \phi_{o(s),\mathcal{C}(s)} + \delta_{m(s)} + \theta_r + \varepsilon_s \tag{4}$$

The outcome variables, y_{rs}, are isomorphic to the job seeker side. In particular, we measure the occupational scope of recruiter r in search s as the number and share of contacted candidates with the last job in recruiters' searched occupation and the average similarity of the last occupations of the contacted candidates with recruiters' searched occupation. As before, the central independent variable is $log(tightness_{o(s),\mathcal{C}(s),t(s)})$, the tightness in recruiters' searched occupation, $o(s)$, the canton or canton group that recruiters specify in the search filter when using the recruitment website, $\mathcal{C}(s)$, and the day of the search, $t(s)$. Our baseline specification includes calendar month fixed effects, $\delta_{m(s)}$, which control for seasonal patterns in the search scope common to all recruiters, and fixed effects for recruiters' search scope, $\phi_{o(s),\mathcal{C}(s)}$, which represent a fixed effect for each combination of searched occupation and the canton(s) specified by the recruiter. Our preferred specification also includes a recruiter fixed effect, $\theta_{r(s)}$, which absorbs all observed and unobserved recruiter characteristics influencing recruiters' scope. This specification absorbs a lot of variation in the data, and identifies the effect of tightness within recruiters and within occupations-region cells. The results are similar, however, in a less restrictive specification that excludes the recruiter

Table 6: Effect of tightness in recruiters' searched occupation on their occupational scope

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	N contacted	N contacted same occ	N contacted diff. occ	Share contacted same occ.	Avg. similarity
log(Tightness)	0.0501 (0.0406)	-0.0501 (0.0368)	0.1779*** (0.0513)	-0.0367*** (0.0068)	-0.2944*** (0.0486)
Calendar month FE	Yes	Yes	Yes	Yes	Yes
Searched occ. x canton scope FE	Yes	Yes	Yes	Yes	Yes
Recruiter FE	Yes	Yes	Yes	Yes	Yes
Family	Poisson	Poisson	Poisson	OLS	OLS
Observations	349,358	340,675	331,653	230,083	230,083
Number of recruiters	22,150	19,408	16,603	22,150	22,150
Pseudo R2 / R2	0.3329	0.2990	0.3042	0.2921	0.5861
Mean of dependent var.	4.037	2.472	1.565	0.6207	13.20

Notes: This table shows regression estimates based on equation 4 of the impact of tightness on recruiters' occupational scope. The estimates in columns (1)–(3) are from Poisson regressions where every search of a recruiter is one observation. Estimates in columns (4)–(5) are from a linear regression on the subset of searches where at least one profile was contacted. Standard errors are clustered at the recruiter level.

fixed effects.[28]

Table 6 reports the results of Poisson and OLS regressions based on equation 4. Column (1) shows that the tightness in an occupation-region cell does not affect the number of job seekers that recruiters contact overall. The same is true if we only count the number of contacted candidates that last worked in recruiters' searched occupation. However, tightness has a statistically significant, positive impact on the number of contacted job seekers who have worked in other occupations (column 3). As a consequence, recruiters contact a substantially lower share of job seekers who last worked in the searched occupation if an occupations is tight (column 4). Column 5 confirms the positive impact of tightness on recruiters' openness as well. It shows that tightness reduces the average similarity between the last occupation of the contacted job seekers and recruiters' searched occupation. Together, these results indicate that recruiters are much more open to job seekers who are willing to change occupations when there is a shortage in the occupation they are seeking to fill.

Figure 7, panel b), illustrates the magnitude of recruiters' flexibility. The top part of the figure uses the regression estimate from column 4, Table 6, and predicts the share of contacted job seekers that last worked in recruiters' searched occupation for tight and slack labor markets. The plot shows that, in a tight occupation (90th percentile of the tightness measure), 55.9% of contacted job seekers have last worked in recruiters' searched occupation. In a slack occupation (10 percentile of the tightness measure), this share is 68.8%. The lower part of the figure shows that recruiters in tight occupation-region cells contact substantially more job seekers from distinct but above-median similar occupations. There is no effect of tightness on the share of job seekers

[28] Such a specification also identifies the effect from the cross-sectional comparison of recruiters that search in the same occupation-region cell.

that last worked in an occupation with below-median similarity to recruiters' searched occupation. Indeed, the baseline probability that recruiters contact such job seekers is low to begin with. These findings suggest that scarcity in an occupation only provides opportunities for job seekers that have last worked in an occupation with a relatively large overlap in job requirements.

Overall, our results imply that recruiters are more selective regarding a job seeker's most recent occupation in slack labor markets. This finding is consistent with the upskilling of vacancies during recessions documented by Deming & Kahn (2018) and with Modestino et al. (2020) who find that skill requirements increase when firms face a larger pool of applicants.

5.4 Heterogeneity

In this subsection, we provide evidence for heterogeneity in the effect of labor market tightness on job seekers' and recruiters' occupational scope along two dimensions: differences between regulated and non-regulated occupations and differences between upward and downward moves along the occupational wage ladder.

5.4.1 Heterogeneity by occupational licensing

In this section, we test whether recruiters and job seekers respond differently to tightness when searching in occupations that require a specific license. We expect that recruiters and job seekers respond less to market tightness if a specific license is required to work in an occupation. The reason is that the need for a license creates lock-in effects: Job seekers from other occupations are less likely to have the necessary requirements to enter the occupation (Kleiner & Xu, in press), and job seekers from the regulated occupation may lose their comparative advantage by moving to another occupation where their license is not valued.

Table 7 shows the effect of tightness on recruiters' and job seekers' occupational scope depending on whether an occupation is regulated or not.[29] Since we have very few recruiters in regulated occupations that conduct several searches with the exact same search terms, we omit the recruiter fixed effects in the recruiter regressions. Conforming to the expectations formulated above, we find that job seekers are more responsive to labor market tightness if they last worked in a non-regulated occupation (panel a, columns 1–2). In regulated occupations, the effect of tightness on job seekers' scope is not significantly different from zero (panel a, columns 3–4). The same is true for recruiters (panel b). In particular, the effect of tightness on recruiters' openness to occupational switchers

[29] We use the 'List of regulated professional activities in Switzerland' published by the State Secretariat for Education, Research and Innovation (SERI, 2022) and manually map the occupations listed to ISCO-08 on the four-digit level.

Figure 8: Search scope response with respect to the occupational wage level: Effect of going from the 10th percentile to the 90th percentile in tightness

(a) Job-seeker (b) Recruiter

Notes: Effects on the predicted probability from our regression estimates. "Tight" indicates that the tightness is set at the 90th percentile of the tightness within the sample. "Slack" indicates the 10th percentile. The effects of control variables are fixed at their mean. The job-seeker regressions in Subfigure (a) control for the calendar month of the click date, for the elapsed spell duration at click (measured in monthly dummies) and for a job seeker fixed effect. The other variables. The recruiter regressions in Subfigure (b) control for the occupation and the canton of the vacancy the recruiter is looking to fill, for the calendar month of the recruiter search and for a recruiter fixed effect.

is entirely driven by non-regulated occupations (column 2). In addition, a look at the means of the dependent variables in panel b of the table reveals that recruiters in non-regulated occupations have a higher baseline probability to contact job seekers from a different occupation compared to recruiters in regulated occupations.[30]

5.4.2 The role of wage differences between occupations

Wage differences across occupations are likely an important determinant of occupational mobility. Several studies examine the relationship between occupational mobility and wage differentials across occupations (e.g., Bachmann et al., 2020; Groes et al., 2015; Altmann et al., 2023). In this subsection, we examine how the effect of tightness on job seekers and recruiters relates to differences in wage levels across occupations.

Figure 8, which is constructed analogously to Figure 7, illustrates how labor market tightness affects job seekers' (panel a) and recruiters' (panel b) occupational scope in terms of wage differences between occupations. As we know from section 5.2, slackness in their last occupations induces job seekers to consider more jobs in other occupations. Figure 8 shows that they venture out more to both, occupations that are lower-paid and occupations that are better-paid than their last

[30]The probability that recruiters contact a job seeker from another occupation is $1.62/(2.43 + 1.62) = 40\%$ in non-regulated occupation. The same fraction is $1.24/(1.24 + 2.67) = 31.7\%$ in regulated occupations.

Table 7: Heterogeneity by occupational licensing

Panel A: Job seeker search behavior

	Non-regulated last occ.		Regulated last occ.	
	(1)	(2)	(3)	(4)
Dependent Var.:	N clicked same occ	N clicked diff. occ	N clicked same occ	N clicked diff. occ
log(Tightness)	0.1082*** (0.0182)	-0.0240** (0.0119)	0.0192 (0.0680)	-0.0209 (0.0254)
Elapsed spell duration	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes
Job seeker (spell)	Yes	Yes	Yes	Yes
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Observations	517,927	610,120	35,380	45,484
Pseudo R2	0.36487	0.33053	0.36819	0.34938
Mean of dependent var.	1.5580	3.6796	1.2259	3.7505
Number of spells	45,849	63,377	4,434	6,079

Panel B: Recruiter behavior

	Non-regulated searched occ.		Regulated searched occ.	
	(1)	(2)	(3)	(4)
Dependent Var.:	N contacted same occ	N contacted diff. occ	N contacted same occ	N contacted diff. occ
log(Tightness)	-0.0280 (0.0525)	0.1844*** (0.0670)	-0.1188 (0.0971)	0.0978 (0.1089)
Calendar month FE	Yes	Yes	Yes	Yes
Searched occ. x canton scope FE	Yes	Yes	Yes	Yes
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Observations	315,230	315,017	61,546	61,266
Pseudo R2	0.15252	0.14782	0.14117	0.12223
Mean of dependent var.	2.4326	1.6278	2.6735	1.2443
Number of recruiters	32,545	8,540	32,545	8,540

Notes: Panel A shows job-seeker behavior Poisson regression estimates of the occupational scope of clicked vacancies on the tightness in the job seeker's last occupation, every search session of a job seeker is one observation. Panel B shows recruiter behavior Poisson regression estimates of the occupational scope of contacted candidates on the tightness in the job seeker's last occupation, every recruiter search is one observation. Subsample analysis by whether the access to the job seeker's last occupations in some form regulated by the government (e.g. occupation licensing). A search session is defined as a day with at least one click. Standard errors are clustered at the unemployment spell level. The tightness measure considers a 30-day rolling window around the job seeker session and recruiter search, respectively. It is defined at the occupation level and only considers the cantons in a job seekers search scope and those fitting a recruiters' location search terms, respectively. Standard errors are clustered at the unemployment spell level.

occupation.

We observe a different pattern for recruiters. We have seen in section 5.3 that recruiters hiring in tight occupations are more open to occupational switchers than recruiters hiring in slack occupations. Figure 8 shows that this is mainly due to recruiters being more likely to contact job seekers from occupations with a lower wage level than the one in their searched occupation. One possible explanation for this pattern is the availability of outside options. Recruiters hiring in tight markets cannot afford to be very selective. Hence, they must consider job seekers willing to work in the occupation, including those who come from lower-paid occupations, although a previous job in a lower-paid occupation may be interpreted as a signal of lower productivity.

6 Conclusion

We analyze recruiters' and job seekers' search activities across occupational boundaries using click data from a recruitment and a job platform merged with administrative data from the Swiss unemployment register. To aid our empirical analyses, we develop a novel measure of occupational similarity based on the average overlap in job requirements between randomly drawn online vacancies.

Our findings suggest that job seekers have a relatively strong preference to remain in their last occupation. The same holds for recruiters: holding the rest of the CV constant, candidates who have last worked in recruiters' searched occupation have a significantly higher chance of being contacted than candidates who last worked in a different occupation. However, the analyses also reveal that overlap in job requirements plays a key role in the search across occupations: if job seekers consider switching occupations, they almost exclusively look at job ads in occupations that are similar in job requirements to their last occupation. Similarly, if recruiters consider job seekers that last worked in a different occupation, they clearly prefer job seekers who last worked in a similar occupation. The power of job requirement overlap to predict job seekers' and recruiters' online search behavior also provides a strong case for the validity of our measure of occupational similarity.

We then use an occupation-region specific measure of labor market tightness to show that both market sides adapt their search strategies in response to scarcity in an occupation. Recruiters that search candidates in a tight occupation, for instance, are substantially more open to considering candidates from other but similar occupations. Workers in, in contrast, are less likely to consider changing occupations if their last occupation is tight.

Overall, our study highlights the importance of job requirement overlap between occupations and labor market tightness in determining the likelihood that job seekers consider changing occupations and that recruiters consider hiring job seekers from other occupations. These analyses shed novel insights into the preferences and behaviors of job seekers and recruiters when searching across occupational boundaries. Ultimately, such information could aid to develop more effective job training and placement programs and help alleviate labor shortages in certain occupations.

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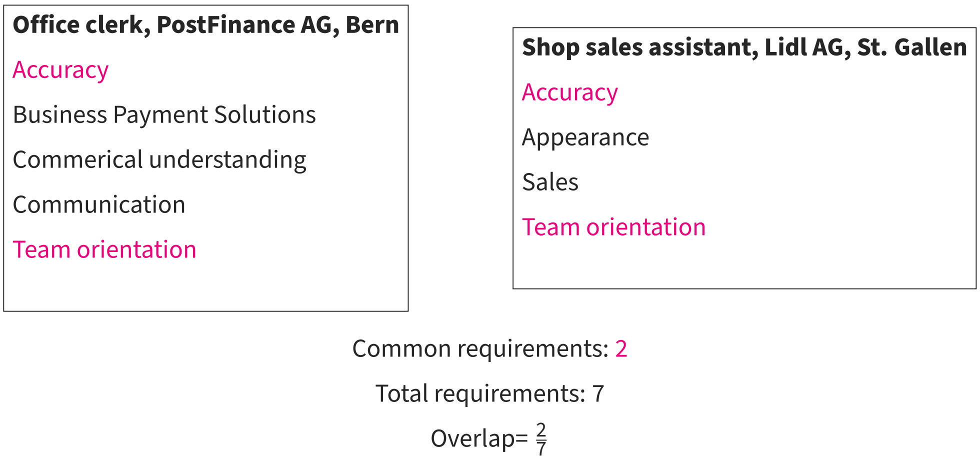
Figure A.1: Job Requirement Overlap Example



Notes: This figure illustrates job requirement overlap between two example vacancies. Source: Own calculations based on X28 vacancy data.

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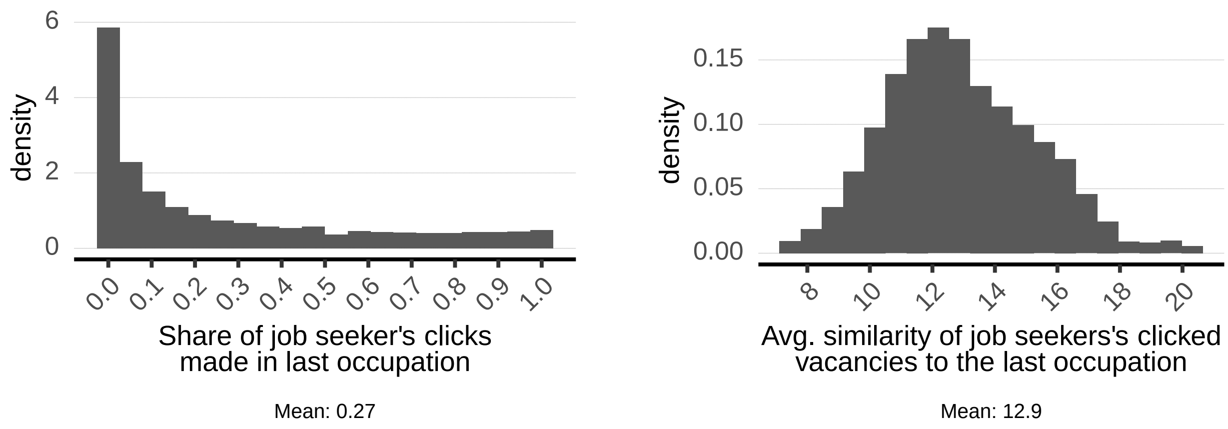
Appendix

Figure A.2: Occupational search scope of jobseekers



The figure illustrates the occupational search scope of jobseekers who search for jobs on Job-Room. The level of observation is an unemployment spell. The left panel shows the share of clicked vacancies where the vacancy occupation matches the occupation of the last job of the jobseeker. The right panel shows the average similarity of the occupations of the clicked vacancies with the occupation in which the jobseeker last worked.

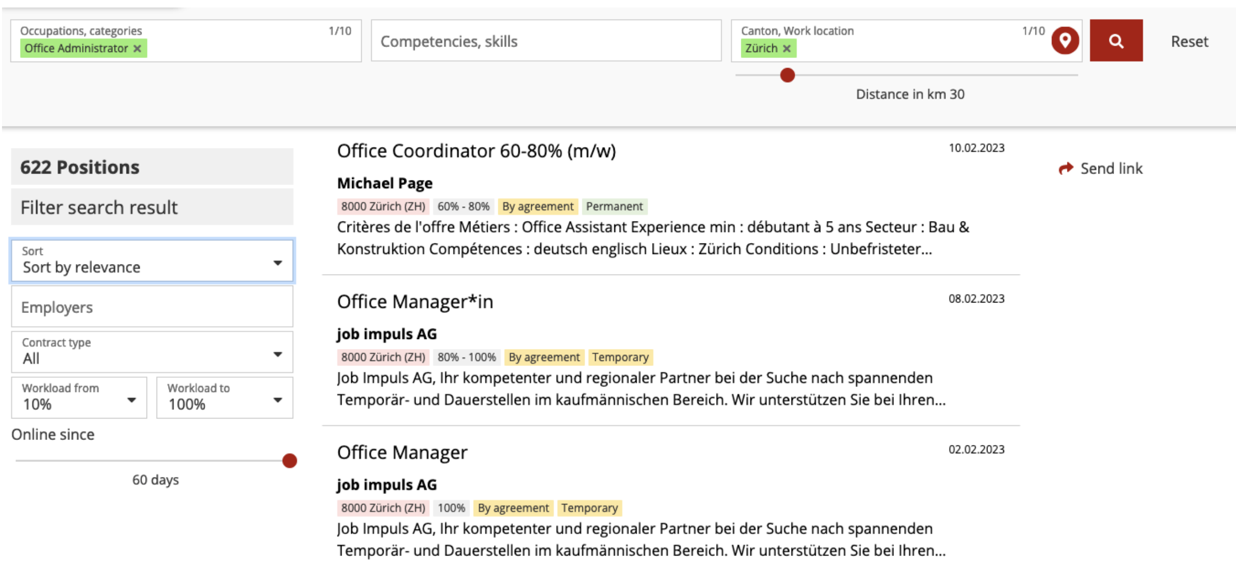
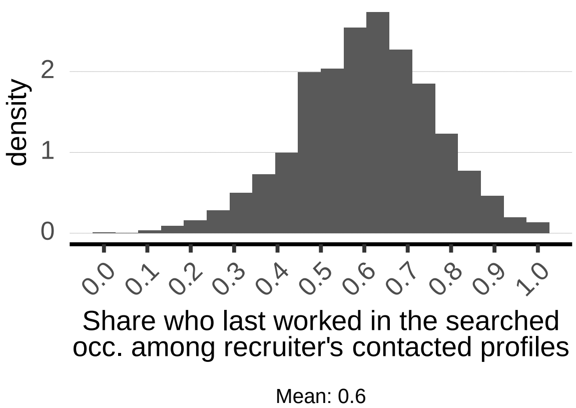
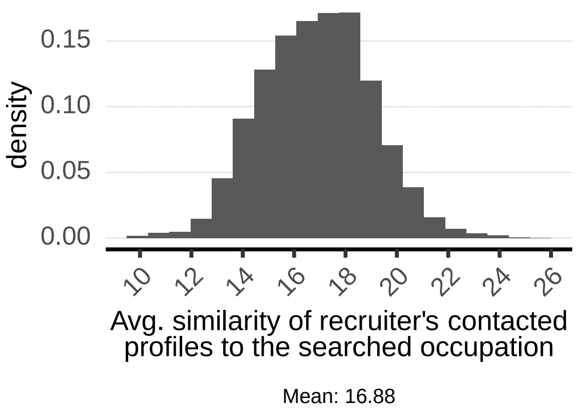


Figure A.3: Screenshot of the job platform of Job-Room.ch after entering "Office Administrator" and "Zurich" into the search mask

Figure A.4: Number of observations used in the regressions, by ISCO-08 1-digit occupation. In the job-seeker regressions, an observation is a click on a vacancy posting in the job-seeker section of job-room.ch. In the recruiter regressions one observation is a click on the button to show a candidate profile's contact details in the candidate search section of job-room.ch

Figure A.5: Occupational search scope of recruiters





The figure shows descriptive evidence on the occupational scope of recruiters. The level of observation is a single recruiter. The Panel on the left shows the share of contacted candidates whose last occupation matches the occupation of the vacancy. The right Panel shows the average similarity of a contacted candidate's last occupation to the occupation of the vacancy.

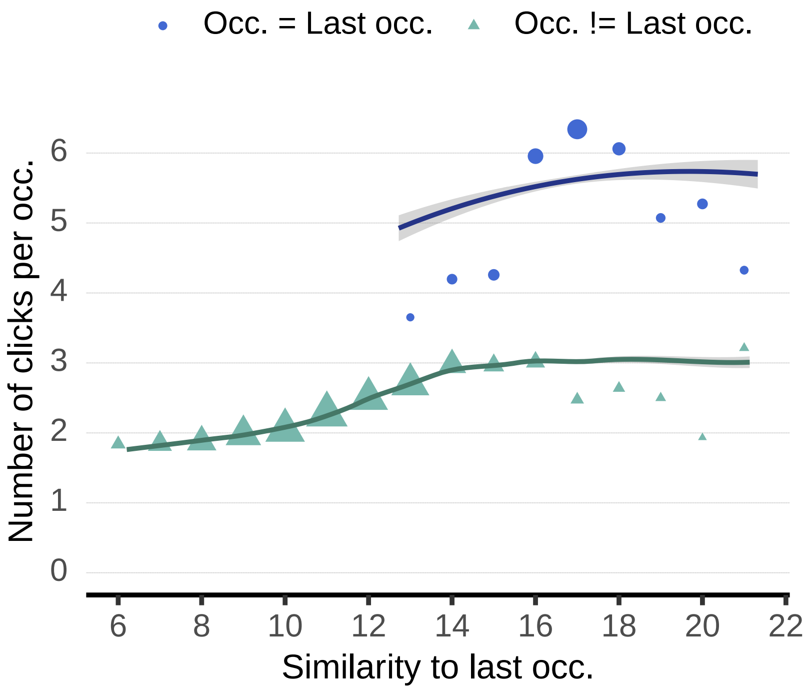
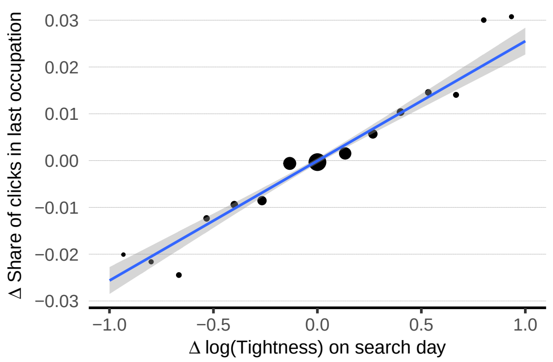
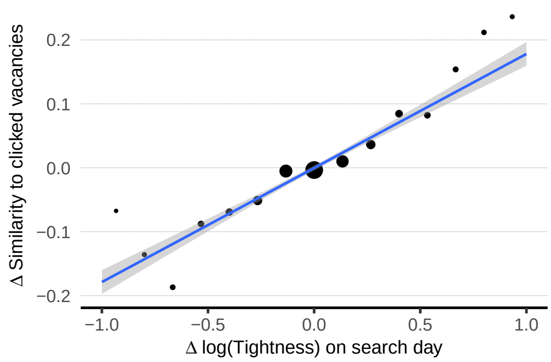


Figure A.6: Binned scatter plot with a local linear regression line: Correlation between the number of clicks in a given occupation, conditional on at least one click in the occupation, and the similarity between the occupation and the job-seeker's last occupation in a given month. The means per bin and the regression line are computed separately for observations where the occupation equals the last occupation and where they are different. The similarity is truncated at the 5th percentile of observations where the last occupation is different from the occupation and at the 95th percentile of the observations where the two occupations are the same. The average contact click probability is 0.0023.

Figure A.7: Relationship between tightness in last occupation and occupational search scope of unemployed job seeker



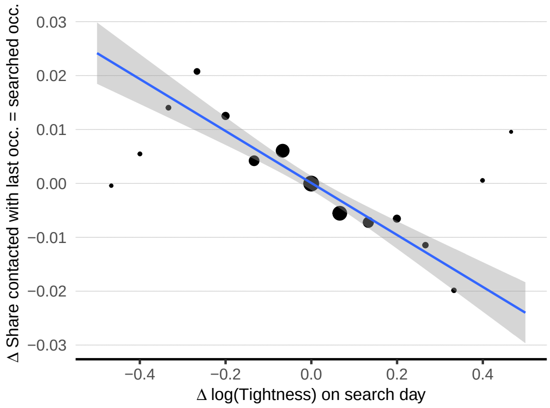
(a) Tightness in last occupation versus share of clicks in last occupation



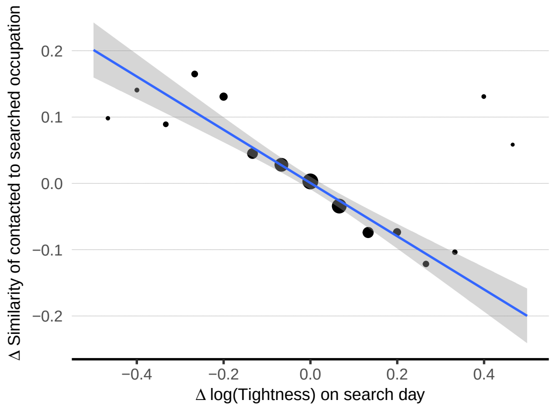
(b) Tightness in last occupation vs average similarity between clicked jobs and last occupation

Notes: Binned scatter plots. Panel (a) relates the log of the tightness measure in a job seeker's last occupation (in the cantonal search scope) to the share of the job seeker's clicks on ads from her last occupation in a search session. A search session is defined as a day with at least one click. Panel (b) relates the log of the tightness measure in a job seeker's last occupation (in the cantonal search scope) to the average similarity between the occupations of the clicked vacancies per day and the last job of a job seeker. All measures are shown in deviations from the job seeker average. The dot size is proportional to the number of search sessions.

Figure A.8: Relationship between tightness in a recruiter's searched occupation and his or her openness to occupational switchers



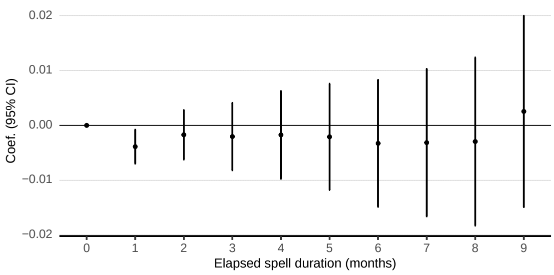
(a) Tightness in recruiters' searched occupation vs share of contacted candidates that last worked in recruiters' searched occupation



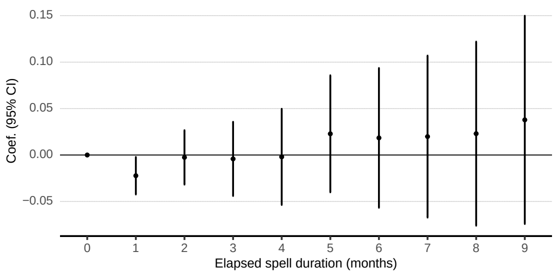
(b) Tightness in searched occupation vs average similarity between contacted candidates' last occupation and recruiters' searched occupation

Notes: Panel (a) relates the log of the tightness measure in the searched occupation and the cantonal scope of the search to the share of the contacted candidates who's last occupation is the same as the searched occupation. Panel (b) relates the log of the tightness measure in the searched occupation and the cantonal scope of the search to the average similarity between the last occupation of the searched candidates and the searched occupation. All measures are shown in deviations from the average over all searches with the same searched occupation and cantonal scope. The plot is conditional on at least one contacted candidate in a search. The dot size is proportional to the number of search sessions.

Figure A.9: Coefficient plot of the dummies for the month of the elapsed spell duration on the occupational scope



(a) Panel A: Effect on the indicator whether the clicked vacancy has the same occupation.



(b) Panel B: Effect on the occupational similarity between the clicked vacancies and the last occupation

This figure plots the coefficients on the elapsed spell duration fixed effects. The regression is the same as Table 5 Columns (4) and (5), regressing the two outcomes on the tightness in the job seeker's last occupation and cantonal search scope in a 30-day window around the search session. The specification controls for calendar month fixed effects based on the day of the search session and for job seeker unemployment spell fixed effects. N = 672,109. Standard errors are clustered at the unemployment spell level.

Table A.1: Job seeker's occupational search scope and the occupation of the new job upon re-employment

	Find job in same occ. as last job			Similarity between found job and last job		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	New occ. = last occ.	New occ. = last occ.	New occ. = last occ.	Similarity	Similarity	Similarity
Share of clicks in last occupation	0.4589*** (0.0097)	0.3973*** (0.0139)	0.3933*** (0.0137)			
Avg. similarity of clicked jobs to last occ.				0.6386*** (0.0107)	0.4582*** (0.0144)	0.4520*** (0.0143)
Secondary or vocational educ.			0.0235* (0.0123)			0.0417 (0.0725)
University educ.			0.0527*** (0.0180)			0.1326 (0.0992)
High experience in last occupation			0.0658*** (0.0092)			0.3892*** (0.0574)
Age = 35-49			0.0159 (0.0103)			0.1188* (0.0607)
Age = 50-64			0.0106 (0.0141)			0.1072 (0.0735)
Female			0.0162 (0.0110)			0.1455** (0.0643)
Receives child benefits			0.0368* (0.0200)			0.3206*** (0.1152)
Constant	0.3228*** (0.0050)			5.756*** (0.1445)		
Last occ. x canton scope FE	No	Yes	Yes	No	Yes	Yes
Last occ. x month of registration FE	No	Yes	Yes	No	Yes	Yes
Observations	21,032	21,032	21,032	21,032	21,032	21,032
R2	0.12248	0.45708	0.46075	0.25080	0.62209	0.62491
Mean of dependent var.	0.48383	0.48383	0.48383	14.388	14.388	14.388

Notes: Regression estimates of the search scope on the portal on alignment between the occupation of the new job after a completed unemployment spell. The sample consists of all spells of registered job seekers with clicks on job-room.ch who completed their spell within 6 months and for whom we know the occupation of the new employment. We know the new occupation for 82% of the completed spells. Column (1) - (3) look at the relation between the share of jobs clicked during the spell and whether the new occupation exactly matches the last occupation before unemployment. Columns (4) - (6) investigate the relationship between similarity of the clicked occupations to the last occupation and the similarity of the new occupation upon re-employment to the last occupation. Standard errors are clustered at the last occupation x canton search scope level.

Table A.2: Robustness: Job seekers's occupational scope of clicked vacancies and tightness in the job seeker's last occupation

Panel A: Share of the clicked vacancies with the same occupation as the job seeker's last occupation

	(1)	(2)	(3)	(4)
Dependent Var.:	Share clicked same occ.	Share clicked same occ.	Share clicked same occ.	Share clicked same occ.
log(Tightness)	0.0128*** (0.0027)	0.0126*** (0.0027)	0.0154*** (0.0020)	0.0159*** (0.0020)
Secondary or vocational educ.		0.0330*** (0.0044)		
University educ.		0.0411*** (0.0061)		
High experience in last occupation		0.0593*** (0.0039)		
Age = 35-49		-0.0259*** (0.0040)		
Age = 50-64		-0.0104** (0.0047)		
Female		-0.0098** (0.0042)		
Receives child benefits		-0.0004 (0.0072)		
Avg distance to clicked jobs (km)				0.0003*** (2.99e-5)
Elapsed spell duration FE	Yes	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes	Yes
Last occupation x canton scope FE	Yes	Yes	No	No
Job seeker spell FE	No	No	Yes	Yes
----------------------------------	-----------------------	-----------------------	-----------------------	-----------------------
Observations	672,109	672,109	672,109	661,518
R2	0.27036	0.27491	0.62430	0.62584
Number of spells	77,843	77,843	77,843	77,140
Mean of dependent var.	0.2964	0.2964	0.2964	0.2961

Panel B: Average similarity of clicked vacancies' occupations to the job seeker's last occupation

	(1)	(2)	(3)	(4)
Dependent Var.:	Avg. similarity	Avg. similarity	Avg. similarity	Avg. similarity
log(Tightness)	0.0661*** (0.0200)	0.0621*** (0.0199)	0.0878*** (0.0146)	0.0916*** (0.0146)
Secondary or vocational educ.		0.1518*** (0.0313)		
University educ.		0.2436*** (0.0422)		
High experience in last occupation		0.4689*** (0.0264)		
Age = 35-49		-0.1268*** (0.0275)		
Age = 50-64		-0.0387 (0.0318)		
Female		0.0274 (0.0290)		
Receives child benefits		-0.0257 (0.0490)		
Avg distance to clicked jobs (km)				0.0009*** (0.0002)
Elapsed spell duration FE	Yes	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes	Yes
Last occupation x canton scope FE	Yes	Yes	No	No
Job seeker spell FE	No	No	Yes	Yes
----------------------------------	-------------------	-------------------	-------------------	-------------------
Observations	672,109	672,109	672,109	661,518
R2	0.36503	0.36973	0.68434	0.68566
Number of spells	77,843	77,843	77,843	77,140
Mean of dependent var.	13.06	13.06	13.06	13.06

Notes: Linear regression of the occupational scope of job seekers search sessions on the tightness in the job-seekers labour market. One observation is a job-seeker session. Sessions are defined as a day with at least one click. The tightness is measured as the number of vacancies divided by the number of jobseekers in the jobseekers' last occupation and the cantons in which the jobseeker is willing to work, as defined in the first meeting with the caseworker at the start of the unemployment spell. The tightness measure considers a 30-day rolling window around the session. Standard errors are clustered at the unemployment spell level.

Table A.3: Job seeker search scope: Disentangling the effects of the components of the tightness measure

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	N clicked	N clicked same occ	N clicked diff. occ	Share clicked same occ.	Avg. similarity
log(N vacancies)	0.0067 (0.0101)	0.1380*** (0.0189)	-0.0215* (0.0112)	0.0155*** (0.0020)	0.0920*** (0.0151)
log(N job seekers)	0.0868* (0.0485)	0.2193*** (0.0788)	0.0661 (0.0557)	-0.0138 (0.0088)	-0.0350 (0.0721)
Elapsed spell duration	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes
Job seeker (spell)	Yes	Yes	Yes	Yes	Yes
Family	Poisson	Poisson	Poisson	OLS	OLS
Observations	672,109	553,307	655,604	672,109	672,109
Number of spells	77,843	50,283	69,456	77,843	77,843
Pseudo R2 / R2	0.2782	0.3656	0.3318	0.6243	0.6843
Mean of dependent var.	4.859	1.537	3.685	0.2964	13.06

Notes: Regression of job seeker vacancy click behavior on the number of vacancies and number of jobseekers in the occupation of the job seeker's last occupation before unemployment. Estimates in Columns (1) - (3) are from a Poisson regression. Estimates in Columns (4)-(5) are from a linear regression. Every search session of a job seeker is one observation. A search session is defined as a day with at least one click. Standard errors are clustered at the unemployment spell level.

Table A.4: The effect of tightness on recruiters' scope: Disentangling the effects of the components of the tightness measure

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	N contacted	N contacted same occ	N contacted diff. occ	Share contacted same occ.	Avg. similarity
log(N vacancies)	0.0736* (0.0392)	0.0445 (0.0373)	0.0964** (0.0482)	0.0005 (0.0073)	-0.0645 (0.0476)
log(N job seekers)	0.0327 (0.0823)	0.3636*** (0.0787)	-0.4870*** (0.1024)	0.1668*** (0.0145)	1.159*** (0.1023)
Calendar month FE	Yes	Yes	Yes	Yes	Yes
Searched occ. x canton scope FE	Yes	Yes	Yes	Yes	Yes
Recruiter FE	Yes	Yes	Yes	Yes	Yes
Family	Poisson	Poisson	Poisson	OLS	OLS
Observations	349,358	340,675	331,653	230,083	230,083
Number of recruiters	22,150	19,408	16,603	22,150	22,150
Pseudo R2 / R2	0.3329	0.2990	0.3042	0.2921	0.5861
Mean of dependent var.	4.037	2.472	1.565	0.6207	13.20

Regression estimates of recruiter contact outcomes on the number of vacancies and the number of job seekers in recruiters' searched occupation. Estimates in Columns (1)–(3) are from Poisson regressions where every search of a recruiter is an observation. Estimates in Columns (4)–(5) are from a linear regression on the subset of searches where at least one profile was contacted.