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THREE ESSAVS ON HOW FIRMS AND WORKERS MEET IN THE LABOR MARKET

KLAEUI Jeremias Samuel

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT D'ÉCONOMIE

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Doctorat en économie

par

Jeremias Samuel KLAEUI

Directeur de thèse
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Three Essays on How Firms and Workers Meet in the Labor Market

sans se prononcer sur les opinions exprimées dans cette thèse.

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Three Essays on how firms and workers meet in the labor market

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Contents

Introduction

The process by which firms and workers connect in the labor market remains largely opaque, frequently referred to as a “blackbox”[1][2]. This blackbox, however, holds significant implications for various aspects of the labor market, including job rates across different types of workers, the balance of power between firms and workers, and labor market flexibility. Understanding how firms and workers meet is crucial for addressing issues such as joblessness and ensuring a dynamic and responsive labor market. The advent of online job platforms has begun to shed light on many stages of this matching process, making previously hidden aspects more observable and measurable. These platforms provide a digital space where, amongst others, jobseekers can search for job postings while employers can post vacancies and search for candidates. They have revolutionized the way jobseekers and employers interact, providing unprecedented access to data on the jobs workers are interested in and on the factors shaping employer’s interest in potential candidates. Leveraging this new information, I aim to delve deeper into the mechanisms of job matching, offering insights into how these processes shape labor market outcomes, employer market power, and the ability of the labor market to adapt to imbalances in labor demand and supply between occupations.

The first chapter of this thesis *Which Job Openings Lead to Employment? The Role of the Consideration Scope in Job Search*, a single-authored study, identifies the set of available job openings that are actually considered by jobseekers, e.g. jobseeker’s consideration sets. I explore how jobseekers’ consideration of job openings relates to employment outcomes. The study utilizes click data from job-room.ch, the Swiss public employment service portal, specifically the clicking behavior on job postings, as an indirect measure of jobseekers’ preferences. Through this lens, I develop an empirical model to predict the types of jobs jobseekers are likely to consider, uncovering notable differences based on gender, education, and previous work experience. These differences result in varied ranges of job consideration, even among jobseekers in identical occupations and geographical areas.

The second important novelty is to show that consideration sets are important determinants of actual job finding. My results suggest that job vacancies have a greater impact on employment chances when they align with the economic sectors that jobseekers most frequently consider, with this effect diminishing for less considered sectors. The jobs that are considered more by a jobseeker

[1] Kircher, P. (2022). Job Search in the 21St Century. Journal of the European Economic Association, 20(6), 2317–2352.

[2] Marinescu, I., & Wolthoff, R. (2020). Opening the Black Box of the Matching Function: The Power of Words. Journal of Labor Economics, 38(2), 535–568

offer them a higher likelihood of getting hired. Job openings in the most considered segments of the economy contribute around 7% to the probability of exiting unemployment within six months.

The third piece of evidence distinguishes broad and narrow search strategies. Broad jobseekers are those who, given their characteristics and the prediction from the job consideration model, are likely to spread their consideration across a wide range of job types. And narrow jobseekers are those who focus their search on a selected segment of the economy. I outline a range of observable characteristics that go along with broad consideration and being able to broadly leverage job openings, for instance, university education, non-Swiss nationality, and being a woman without childcare obligations. On the other hand, having children or a high level of occupation-specific skills through vocational education or long tenure in a single occupation goes along with narrow, focused consideration. The study shows that a broader consideration is not necessarily associated with better job finding. Instead, jobseekers with a more focused consideration set can better leverage the job openings within that narrower scope compared to their counterparts who distribute their consideration more broadly. This result comes with policy implications for unemployment agencies. If employment services advise narrow jobseekers to search broadly, this may divert their attention to segments of the market with a lower job-finding probability for them. Hence, job search advice to broaden the search scope, as advocated frequently in the recent literature, is not necessarily beneficial.

The second chapter, *Job Search and Employer Market Power*, is a joint effort with Ihsaan Bassier and Alan Manning of the London School of Economics and Political Science. It uses the same click data as the first chapter to investigate the link between the way workers search for jobs and the power relations between firms and workers in the labor market. Given the overwhelming number of jobs available in the economy at any given time, it is rational for jobseekers not to consider them all but to focus on a limited set of options. This has implications for the bargaining power of employers over workers and the wages set by employers. Existing models of employer market power make implicit assumptions about the shape and size of this set of considered job options. The seminal search model by Burdett and Mortensen posits that workers encounter jobs occasionally and one at a time, implying they have at most two employment possibilities at any moment. Conversely, models with idiosyncratic preferences over jobs — the second large strand of employer market power models — view jobs as imperfect substitutes whilst assuming workers can choose from the full set of employers. Recognizing the significance of consideration sets in the determination of employer market power, this study develops a model linking firm market power to the size of workers' choice sets. Our model encompasses job search by assuming job opportunities arise sporadically, but workers' consideration sets may include multiple options, not necessarily all jobs in the market. The study demonstrates that market power depends on both the extensive margin (job opportunity arrival rate) and the intensive margin (size of consideration sets).

Using the job search data from the official portal of the Swiss Public Employment services, we introduce a novel measure of employer market power, akin to the Herfindahl-Hirschman Index (HHI), focusing on vacancy-level employer competition for workers. The index is derived from our theoretical model and uses empirical estimates of the number and type of job options considered based on jobseekers' clicks on job postings and their job-finding rates. The study also discusses policy implications, noting that labor market competitiveness depends on the average jobseeker's consideration set. Individual jobseekers lack incentives to broaden their search to improve market competitiveness, as their efforts minimally impact overall competitiveness. This insight impacts policies on job search advice. If public employment services can encourage jobseekers to consider more options and if these options are similar in quality to the already considered jobs, this can increase competition among firms for candidates and reduce employer market power.

The third chapter is joint work with Rafael Lalive, Daniel Kopp, and Michael Siegenthaler: *Adapting to Scarcity: Job Search and Recruiting Across Occupational Boundaries*. In this study, we examine whether the search horizons in the labor market respond to market circumstances. Such responsiveness would enhances the market's ability to react to disruptions such as labor scarcities or technological change. In this study, we not only look at the clicks by jobseekers but also analyze recruiters' clicking behavior on the Swiss Public Employment Services job portal. The recruiters see standardized profiles of jobseekers and decide whether to contact them for an interview.

First, we develop a new, broadly applicable measure of overlap between and within occupations based on job requirements stated in vacancy postings. This measure allows us to investigate the role of task and job requirement overlap in facilitating occupational mobility. Innovatively, we also measure the similarity of job requirements within an occupation between different jobs, acknowledging that there might be heterogeneity even within detailed occupations and that not all occupations are defined with the same level of specificity; some occupations have broader, less concrete definitions, while others are more narrowly and precisely defined.

Second, we quantify how job requirements overlap and jobseekers' last occupation influence search behaviors on both sides of the labor market. Our findings indicate that jobseekers search well across occupational boundaries and are significantly more likely to consider jobs with a higher overlap in requirements with their last occupation. Recruiters prioritize candidates with experience in the target occupation but also contact candidates with experience in occupations that have a high overlap in job requirements to their target occupation.

Third, we explore how jobseekers and recruiters adjust their occupational search scopes in response to labor market tightness. Labor market tightness is measured by the number of vacancies per jobseeker. For example, when a labor market becomes tight — when jobseekers are scarce compared to job opportunities — we find that jobseekers tend to focus more on their last occupation. Conversely, recruiters facing tighter labor markets, characterized by a higher ratio of vacancies to jobseekers, become more willing to consider candidates from other occupations with similar job requirements. This responsiveness to market conditions indicates an adaptive behavior that can enhance labor market efficiency. These insights are crucial for developing strategies that support workers in transitioning between occupations and for ensuring that employers can find suitable candidates in a dynamic labor market. Additionally, our empirical measure of occupational similarity can inform policies and interventions aimed at improving job matching and labor market efficiency.

In summary, this thesis sheds light on the "blackbox" in which firms and workers connect. By leveraging novel online click data from both jobseekers and recruiters, my co-authors and I help uncover aspects of job matching and the factors influencing job consideration sets, employer market power, and labor market responsiveness to supply and demand imbalances. The findings highlight the substantial role of consideration sets in job search outcomes and employer bargaining power and demonstrate that both jobseekers and recruiters adjust their behaviors in response to labor market conditions. The insights gained from this research have significant policy implications, helping to guide which types of interventions can enhance job matching efficiency, increase labor market competition, and support workers in their occupational transitions.

CHAPTER 1

Which Job Openings Lead to Employment? The Role of the Consideration Scope in Job Search

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University of Lausanne

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Abstract

I investigate job market matching, analyzing how jobseekers distribute their consideration over different segments of the economy and how this affects which job openings help them find employment. Utilizing clicks on an online job portal as a proxy for job consideration, I estimate a differentiated jobs model of which jobs jobseekers are likely to consider, revealing significant heterogeneity based on gender, education, and labor market history. This heterogeneity leads to different consideration scopes, even for two workers located in the same occupation and commuting zone. I examine the effect of job openings on job finding in a monthly hazard regression. The job openings are categorized by their likelihood of jobseeker consideration predicted by my model. I show that the effects of job openings on job finding are highest for openings in a worker's most considered segments of the economy and decrease with lower predicted consideration. To isolate variation in labor demand from labor supply factors, mass-hiring events are introduced as a measure of job openings. Finally, I differentiate between broad and narrow jobseekers. Broad jobseekers have positive job-finding elasticities to a wider range of job openings than narrow jobseekers. However, the narrow jobseekers, who focus their consideration on few segments of the economy, have much higher job finding elasticities from openings in those segments. I discuss implications for place-based policies and job-search advice.

Keywords: job search scope, job consideration, labor supply, matching.

JEL Codes: J22, J24, J60

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1 Introduction

Labor demand and supply do not always align. Many times, new job openings call for occupations that jobseekers have no experience in, or they arise in locations distant from where jobseekers live. Governments around the world allocate vast funds to foster job creation, frequently with the idea of bringing jobs closer to areas with high unemployment[1]. Similarly, there is a growing literature trying to expand the occupational and geographical scope of jobs that the unemployed consider, with the aim to increase their job-finding chances (for an overview see Kircher, 2022). However, how broad jobseekers actually are in their consideration and how this interacts with their ability to match with job openings is not fully understood.

Writing and sending applications is costly, so jobseekers will only apply for a job if the job is attractive enough and the prospect of receiving an offer is promising enough. But even this knowledge is not readily available: jobseekers need to gather information about which jobs are worth applying for. The importance of this decision is exacerbated by the fact that vacancies are almost always advertised in a specific occupation and for a specific location, even if they might accept jobseekers from outside this location or occupational switchers[2]. I use click data as a measure for this decision, which I call the "consideration" decision[3].

What types of jobs are considered by a jobseeker is the first question posed in this paper. This will indicate which jobs, in the eyes of a jobseeker, are expected to be attractive enough and have a high enough chance of getting them that he or she wants to learn more about them. I use a dataset of clicks made by registered unemployed on job postings on job-room.ch, the official job portal of the Swiss public employment service, to estimate a discrete choice model of what factors influence whether a jobseeker considers a job. The clicks made can be linked to data on the jobseekers' characteristics from their unemployment records. I leverage this information to show how the importance of different factors varies over different types of workers, even if they last worked in the

[1]E.g. Moretti (2011); Manning & Petrongolo (2017); Gathmann et al. (2018). The European Regional Development Fund dispenses €50 billion yearly to assist struggling regions and companies Gathmann et al. (2018). Switzerland's New Regional Policy targets rural and border areas, aiming to create jobs. From 2016 to 2023, it provided CHF 720 million in support, combining grants and loans. Additionally, it subsidizes tax cuts by local governments to industrial companies or production-related service companies SECO (2023).

[2]For instance, on the official job portal of the Swiss employment services, only 3% of vacancies state more than one occupation, while 52% of Swiss unemployed find a job outside of the narrowly defined 4-digit ISCO occupation of their last employment (Klaeui et al., 2023).

[3]In the marketing and IO literature, modeling consideration is common, and considering a product is usually based on its expected utility before "considering" it and finding out more about it (Honka et al., 2019; Ursu et al., 2022). In the directed job search literature (for an overview see Wright et al., 2021), decisions are based on the expected utility of a job, defined as the product of the utility of working a job (v) and the probability of getting the job (π). Combining this yields that the job consideration decision is based on the expectation of the expected utility ($E[\pi v]$). For instance, when we think of an economy with many segments of jobs (e.g., occupations or locations), a jobseeker's consideration decision would depend on the expectation over the distribution of πv within the segment.

same occupation and live in the same region.

Second, I explore if the jobs jobseekers are interested in are the ones where they are most likely to get hired. This helps to understand if jobseekers' expectations match the real job opportunities. To answer this question, I create a monthly panel from the administrative data on spells of the Swiss unemployed and merge this with a third dataset of comprehensive online vacancy data. The estimates from the discrete choice model are used to categorize the job openings based on their likelihood of consideration by the jobseeker.

The third question is about search breadth. As people differ in the jobs they consider, they also differ in their search scope. I distinguish between two types of jobseekers, 'broad' jobseekers, who consider a wide range of different types of jobs and 'narrow' jobseekers who focus their consideration on a selected segment of the economy. I investigate whether these differences in search scope vary systematically among different characteristics, such as gender, education or their labor market history. Finally, I explore if these differences in search scope align with segments of the economy where the probability of finding a match is high.

I start by estimating the discrete choice model, which jobs jobseekers click on. In that model, I compare the importance of three dimensions of alignment between the jobseeker and the job: i) the commuting time to the job, ii) whether the job's occupation matches the jobseeker's last occupation before unemployment, and iii) whether the job's hours match the jobseeker's workload preferences. The fourth dimension is a job-specific constant that, among other things, captures any information related to the wage level (wages are almost never posted in Switzerland). I further control for the number of days a vacancy was online at the time of the click. I also interact the three measures of alignment with a range of personal characteristics such as gender, education, nationality, or occupation-specific experience to investigate how personal characteristics affect the importance of the different dimensions. Recent studies have examined several dimensions of what types of jobs people search for and how search varies over different groups of workers (for instance Marinescu & Rathelot, 2018; Banfi et al., 2019; Le Barbanchon et al., 2021; Fluchtmann et al., 2022; Philippe & Skandalis, 2023). My contribution is to compare the most important dimensions in a unified framework.

In my estimation of which jobs workers click on, I further extend an emerging strand of literature that employs methods commonly used in consumer choice research to estimate jobseeker's preferences over jobs (Hirsch et al., 2021; Azar, Berry, & Marinescu, 2022; Roussille & Scuderi, 2023). Similar to Azar, Berry, & Marinescu (2022), I estimate a nested logit model, dividing the labor market into many small nests, which I call 'submarkets'. I define submarkets as the combination of a job's occupation (ISCO 3-digit), the job's hours worked (full-time vs. part-time), and the job's location (granular sub-unit of commuting zones). At the median, submarkets contain around 20 vacancies at a given point in time. First, workers decide which submarkets they consider (the top-level logit). Second, jobseekers choose which jobs to click on within these selected submarkets markets (the bottom level logit)[4].

My estimates suggest that occupational match and distance between home and the workplace are the most important factors in shaping job consideration, dominating differences in job-specific constants between jobs with the same location and occupation. There is sizeable heterogeneity in how personal characteristics shape job consideration. For instance, women put a higher weight on short commutes compared to the job-specific constants, in line with the finding by Le Barbanchon et al. (2021), who show that women are more willing to trade-off higher wages for a shorter commute. I extend upon their results, showing that women are also more willing to trade off occupational match for shorter commutes. I further show that jobseekers with university education have a much larger flexibility in working far from home compared to workers with secondary education. Jobseekers with a high level of occupation-specific experience are less open to jobs outside their last occupation. The heterogeneity in the importance of different dimensions for different workers implies that even workers with the same occupation and living in the same commuting zone can have vastly different consideration scopes. On average, two people with the same commuting zone and occupation share only 3 of their 10 most considered submarkets.

My second contribution is to investigate how workers' consideration scopes relate to their job-finding chances. Estimating the effect of a person's consideration scope on job-finding comes with two major empirical challenges. The first is that people who differ in their consideration also differ in other aspects, such as their personal characteristics, and these aspects also shape the employability of the person, leading to omitted variable bias. To tackle this problem, I don't directly measure the effect of consideration on job finding: I exploit vacancy-level data on characteristics of new jobs combined with my consideration estimates to test whether job openings have a higher impact on a jobseeker's exit chances if the jobseeker is more likely to consider them. The dependent variable of my regression is the monthly hazard of exiting unemployment. The explaining variables are the 3-month rolling averages of the number of vacancies categorized according to the predicted likelihood that the jobseeker will consider the vacancy's submarket. This setup allows me to test the influence

[4] The nested logit structure efficiently manages the complexity of estimating a choice between all jobs available on the platform, between 70'000 and 110'000 at a given point of time: The bottom-level logit models a conditional click probability and only needs to be estimated for jobseekers clicking in a submarket, greatly reducing computational complexity.

of job consideration while holding observable personal characteristics constant by controlling for their direct effect on job finding in my regression.

However, there is still a concern about unobservable jobseeker characteristics jointly influencing the consideration scope and the job finding. To tackle it, I don't directly use a jobseeker's consideration scope, but I use a prediction based on the search scope of other jobseekers with similar observable characteristics. Specifically, I split the sample of jobseekers into two. In one sample, I estimate the job consideration model described above using the jobseekers' clicks. The estimation allows for heterogeneity over nine dimensions of personal characteristics, leading to almost individual-specific predictions. I apply the predictions to the other sample, the main regression sample. In that sample, I regress the individual exit hazard on the number of job openins, interacted with the *predicted* consideration. In such a setup, only the variables used in the consideration model enter the predicted consideration. In other words, the selection into how likely a jobseeker is to consider a job is only based on observables, and I control for all those observables in my regression. In my baseline specification, I control for personal characteristics, the last occupation and residence location fixed effects, as well as for time trends and duration dependency.

To measure job openings, I use vacancy data from X28, a daily web scraped dataset of the near-universe of online job postings. The data has previously been used in research (Lu et al., 2020, 2021; Colella, 2022; Buggle et al., 2023) and policy work (Arni, 2020; L. Liechti et al., 2022; Bannert et al., 2022; Kaiser et al., 2023).

My baseline results show that, indeed, the job openings in the ten submarkets with the highest predicted consideration probability have the highest effect on job finding. For the average jobseeker, the job openings in the ten most considered submarkets contribute around 7% to the probability of leaving unemployment within six months. To compare, having university education contributes 1.8%, and having a child or not explains 16% of the six-month hazard rate. Job openings in the 11-20th ranked submarkets have a smaller but still positive contribution of around 2%. The effect is insignificant beyond the 20th rank. The results are robust to controlling for the number of jobseekers also searching in the submarkets, including occupation-specific time trends, and controlling for search intensity using the number of applications recorded in the unemployment register.

The second major empirical concern is reverse causality in the relationship between job postings and job consideration: Firms might strategically post their vacancies in submarkets that are considered by many workers. I address this concern by introducing firm-level mass-hiring events as a measure of job openings. Such events, where firms want to fill a lot of positions at once, are likely to be driven by broader product market shifts and to be independent of the distribution of jobseekers.[5] The results from the mass-hiring specification confirm the patterns observed in the baseline analysis, with effect sizes very similar to the baseline estimates.

In a complementary analysis, I combine the firm-level mass-hiring data with administrative data on the name of the firm of the first job upon re-employment. This data allows an even more detailed estimation: whether a jobseeker finds a job at the hiring firm. Remarkably, the estimation can identify the single occupation $\times$ location $\times$ workload submarket in which a job opening will have the most influence. The results confirm the gradual decay of the effect of job openings based on jobseekers' consideration probabilities. A mass-hiring event leading to 5 vacancies in a jobseeker's most considered submarket increases the jobseeker's chances of finding a job at that firm by 293%. The effect of five created vacancies in the second most considered submarket is 178%, and comparing the effects for less considered submarkets shows a gradual decay.

The third key contribution of my paper is to distinguish between two types of jobseekers. I differentiate between broad jobseekers, who, based on their characteristics and the prediction from the job consideration model are likely to spread their consideration across a wide range of submarkets and narrow jobseekers, who are likely to focus their search on few submarkets. Jobseekers who are likely to have narrow consideration are workers with secondary or vocational education, workers with high occupation-specific experience and parents whose children live in the same household, especially mothers. Broad consideration is associated with university education, non-Swiss nationality and women without children. I find that the broad type benefits from job openings in a wider range of submarkets: They experience substantial job finding effects from openings in their twenty most considered submarkets. Conversely, the narrow-type jobseekers only witness positive job finding effects from openings within their ten most considered submarkets. However, this smaller radius is more than offset by the extent to which the narrow jobseekers can leverage those job openings. The job finding elasticity with respect to job openings in their top ten submarkets is twice as large compared to the elasticity observed for broad jobseekers. This substantial difference is robust to controlling for search intensity, occupation-specific time-trends and the number of jobseekers.

Conditional on consideration, finding employment from job openings in a submarket is more likely if either the match probability is higher for the typical job in the submarket or if there simply are more jobs in the submarketFor a given number of job openings, the narrow jobseekers have

[5]Following Jacobson et al. (1993), mass *layoffs* are often utilized as an exogenous measure of job loss. Similarly, in my study, mass-*hiring* events are treated as an exogenous shock to local labor demand. Further, my measure has parallels to Bassier et al. (2023) who use sharp changes in wages reported in a firm's online vacancies. I use sharp changes in the number of a firm's online vacancies.

higher job finding probabilities from openings in their most considered submarkets than broad job seekers. This suggests that the characteristics that make job seekers likely to consider jobs narrowly also make them have a higher match probability with the jobs "close" to them. Applying this conclusion implies that policies aimed at improving job finding may have varying impacts depending on the jobseekers' type, whether they are narrow or broad. Hence, advising jobseekers with narrow-type characteristics to consider jobs more broadly may not have big welfare benefits: the jobseekers could have a low probability of a good match from those jobs. At the same time, place- or occupation-based policies leading to job creation in the narrow jobseekers' most considered submarkets are likely to have large effects on the number of matches and match quality. For broad-type jobseekers the opposite applies: they will benefit less from jobs created 'close' to them in terms of occupation, geography or workload but they are able to leverage jobs broadly: good advice which specific segments of the economy to consider can be of high value to them.

Contributions to the literature. A strand of the literature explicitly focuses on the size and boundaries of local labor markets (Schmutte, 2014; Manning & Petrongolo, 2017; Goos et al., 2019; Nimczik, 2020). I extend the literature by looking at a direct measure of job search, jobseeker clicks. My results confirm the studies' findings that labor markets are local and not strictly confined by traditional occupational or geographical boundaries. My second contribution is investigating the role of personal characteristics and showing that individuals with identical occupations and locations can have distinctly different labor markets.

Another strand of literature has implemented job search advice in several interventions aiming to widen the job consideration scope of job seekers, reaching ambiguous conclusions (Belot et al., 2018, 2022; Dhia et al., 2022; van der Klaauw & Vethaak, 2022; Altmann et al., 2022; Barbanchon et al., 2023). My research contributes empirical evidence into how job seekers actually distribute their consideration across various job dimensions, illuminating the underlying patterns the studies try to affect. I distinguish between broad and narrow job seekers, show differential job-finding elasticities to job openings, and discuss implications for such interventions. Kircher (2022) makes the theoretical argument that optimal job search advice should equate the labor market tightness in all segments of the economy. I provide empirical evidence that the match rate indeed increases concavely with the number of vacancies and decreases with the competition, even in granular segments of the economy.

Marinescu & Rathelot (2018); Banfi et al. (2019); Le Barbanchon et al. (2021); Fluchtmann et al. (2022) and Philippe & Skandalis (2023) look at non-wage job characteristics driving applications.

I contribute to the strand by i) showing results for the earlier clicking stage, where many initial decisions are made, ii) by accounting for the availability of different types of jobs using a discrete choice model and iii) by comparing many of the personal characteristics and dimensions looked at in the literature in a unified framework.

Many studies such as Banfi & Villena-Roldan (2019); Marinescu & Wolthoff (2020); Hirsch et al. (2021) who investigate the role of wages in attracting applicants need to assume some set of relevant alternatives to the jobseekers. They do so using clustering, the job title, and all jobs in Hamburg, respectively. I use data to measure consideration and contribute estimates of how likely jobseekers are to consider jobs on a very granular occupation $\times$ location $\times$ part-time level, potentially helping to guide such research decisions in the future. My measures are validated by my analysis of the effect of job openings on job finding, showing the predictive power of my consideration estimates.

Methodologically, my job consideration model contributes to the studies using discrete choice models to analyze job choices (Hirsch et al., 2021; Azar, Berry, & Marinescu, 2022; Mauri & Zuchuat, 2023; Roussille & Scuderi, 2023; Caldwell & Danieli, 2024). My estimation of the effect of job postings contributes to the papers using the link between market tightness and job finding to measure relevant market segments for workers (Manning & Petrongolo, 2017; Goos et al., 2019) and extends the strand using mass-layoffs as an exogenous measure for quits by using mass-hiring as an exogenous measure for local job creation (Jacobson et al., 1993; Charles & Jr, 2004; Sullivan & Wachter, 2009; Couch & Placzek, 2010; Ananat et al., 2017; Ost et al., 2018; Grübl et al., 2020; Moretti & Yi, 2024).

The rest of the paper proceeds as follows. Section 2 presents the data used and descriptive statistics. Section 3 details the estimation of job consideration. Section 4 is about the heterogeneity in job consideration. In Section 5, I explore the interplay of job openings and consideration and Section 6 analyzes how the scope of jobseeker consideration influences their job finding rates. Lastly, Section 7 summarizes and discusses policy implications.

2 Data and Descriptives

My study combines data from three different sources, i) administrative data about unemployed jobseekers in the Swiss unemployment register, ii) click data from job-room, the official job portal of the Swiss employment services, iii) data on the near-universe of online vacancies from X28, a webscraping company.

2.1 Definitions used

The location is specified as sub-units of commuting zones segmenting commuting zones into 2 to 12 granular locations. This definition comes from the Swiss Federal Statistical Office (SFSO). The SFSO defines commuting zones as areas in which the majority of the working population lives and works, based on the matrix of commuter flows between all Swiss municipalities. Those commuting zones are subdivided again so that the labor market regions are 'as spatially comparable as possible' (SFSO, 2018). In this way, a total of 101 labor market locations are defined. For the occupation, I employ the International Standard Classification of Occupations (ISCO) by the International labor Organization. The classification is hierarchical with increasing granularity. I use the three-digit-level – the second most granular level – which contains 119 different occupations with at least one click on the job-room. For the hours worked, I differentiate between two categories, part-time and full-time jobs. A full-time job usually entails 40-42 hours per week, and in Switzerland it is common to report the workload as a percentage of a full-time job. I classify a job as part-time if the indicated percentage is 80% or lower.

2.2 Unemployment Register Records

The dataset encompasses information on all jobseekers registered with the Swiss unemployment services during the period from July 1, 2018, to June 30, 2021. It includes detailed records such as the start and end dates of unemployment spells, whether the spell concluded with job finding, and the company name of the new employer. Additionally, the data covers demographic details like age and gender, municipality of residence, residential permit status including Swiss nationality, and the number of dependents below 18 living in the same household. Also documented are the highest level of education attained by the jobseeker an indicator of experience level in the most recent occupation (< 1 year, $1-3$ years, > 3 years), and the amount of the last salary insured with the unemployment insurance before the onset of unemployment.

The unemployment register data includes the occupational labor market history of every jobseeker. I will define a jobseeker's occupation as the occupation of the jobseeker's last job before unemployment. The occupation is reported in an internal classification used by the Swiss employment services but also using the ISCO. When a jobseeker registers as unemployed, in the first meeting with the caseworker, they are asked to indicate their preference for hours worked. This indication has implications for the benefits a jobseeker receives. If a jobseeker indicates that she is willing to work full-time, she has to accept an otherwise suitable offer for a full-time job otherwise she are subject to benefit sanctions. If she receives an offer for an, otherwise suitable, part-time job, she is still entitled to benefits. Conversely, if a jobseeker indicates that he is looking for a part-time job, he does not have to apply for or accept offers of jobs with a higher workload than indicated. Hence, this indication of workload preference has real-world implications for jobseekers and is more than an survey question. The options they can indicate is a percentage of a full-time job. A full-time job usually corresponds to 40-42 hours per week. I classify a jobseeker as seeking for a part-time job if the indicated percentage is 80% or lower.

2.3 Commuting times

I obtain the travel distance between municipalities from openrouteservices.org, by the Heidelberg Institute for Geoinformation Technology at Heidelberg University. Openrouteservices.org is a service that uses OpenStreetMap data to calculate travel distances between two points. I use the 'driving-car' mode of transport, which is the default mode of transport in the service. While many people in Switzerland use trains and other public transport for their commutes, train travel times are much harder to obtain and tend to correlate highly with car driving times. I extract the shortest car travel distance between the centroids of the two municipalities. I obtain the centroids from map shapefiles from the Swiss Federal Statistical Office. If the municipality of residence and the municipality of a job are the same, I pick 50 random points within the municipality and calculate the average distance between them. I map the municipalities to the local labor market locations used in the analysis using the official crosswalk. To compute the travel time between a jobseeker's home and a labor market location, I take a weighted average of the travel times between the location of residence and the municipalities in the labor market location, where the weights are the number of vacancies in each municipality.

2.3.1 Job Search Process on job-room.ch

Job-room.ch operates as the official job portal of the Swiss public employment service, and is available in German, French, Italian, and English. The portal aggregates its listings from two primary sources: 1) direct postings on the portal, which can be posted there by companies and are free of charge. 2) Job postings scraped from other job portals, with the aim to cover as much of the labor market as possible. While job-room.ch aims to provide a comprehensive representation of job vacancies in Switzerland, it may not achieve complete coverage. It is recognized that many vacancies on job-room.ch are also listed on other platforms, indicating that the data from this portal captures only a portion of a jobseeker's total job search activity. Usually, there are between 70'000

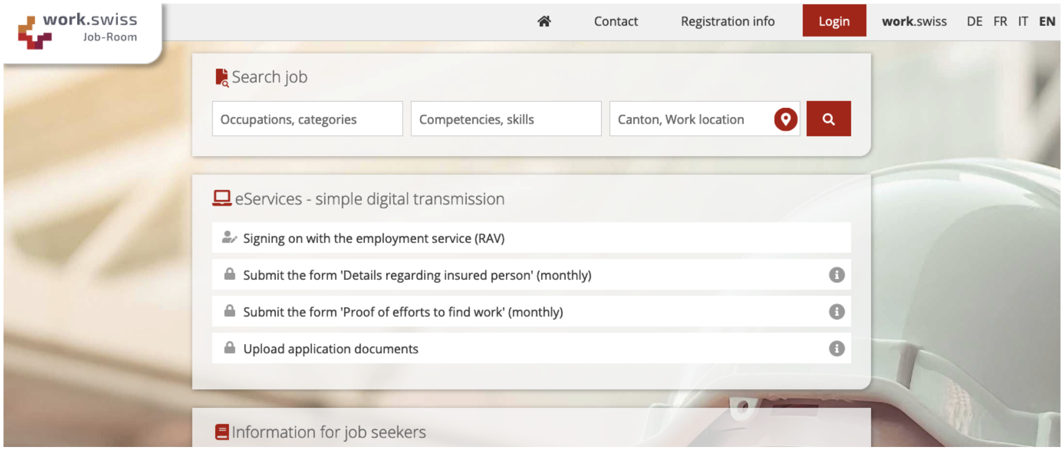


Figure 1: Screenshot job-room.ch.

Screenshot of the starting page of the job search portal, `https://job-room.ch/home/job-seeker`. Screenshot taken 10-02-2023

and 110'000 job postings on the portal [6]. In addition to job listings, job-room.ch offers features for the unemployed. Registered users can log their application protocols, which is a requirement for receiving unemployment benefits. Job-room thus provides a convenient way to both, manage their unemployment spell and also search for jobs.

The portal's interface requires jobseekers to specify criteria such as occupation, competencies or skills, and work canton or municipality. See Figure 1 for a Screenshot. Based on these criteria, jobseekers are presented with a list of relevant job vacancies. To access detailed information about a vacancy and potentially apply, jobseekers must click on the respective listing. These clicks, central to this study, represent the jobs of interest to the jobseeker. As an example, a search input for the occupation "Office managers" in the "Zurich" location would yield a set of relevant vacancies, as shown in Figure 2. The subsequent clicks shows the content of the vacancy and information how to apply. I do not observe the queries entered into the search field nor the result list. One interpretation of the clicks is therefore that they are a measure of the occupation, location and other search criteria entered in the search field. A search (e.g for an occupation or location) only yields results that exactly match the search criteria. When entering search terms, the jobseeker is provided with a auto-completion suggestions. Those suggestions come from several definitions of the occupation (ISCO and several internal lists) and location (municipality and canton). Those definitons vary in how broad they are.

[6] An empty search on `https://job-room.ch/home/job-seeker`, with no criteria specified, yields the full number of postings avaiable.

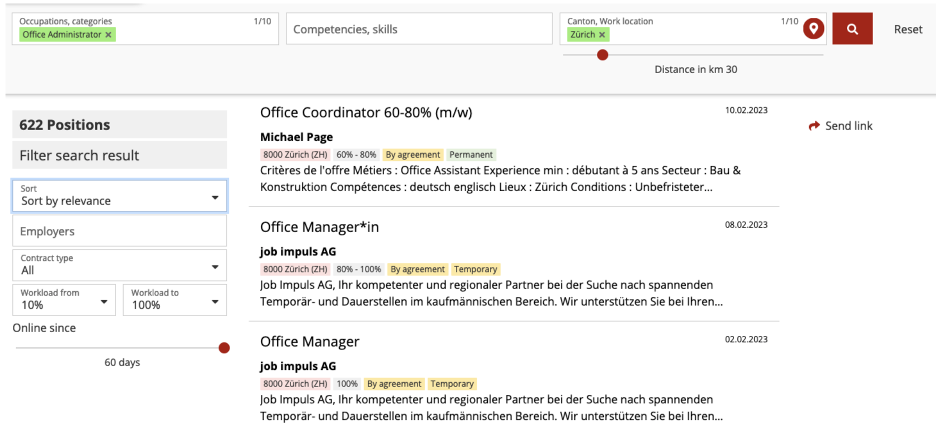


Figure 2: Screenshot of the result list when searching for "Office managers" in Zurich on the job room (`https://job-room.ch/home/job-seeker`). Screenshot taken 10-02-2023.

2.4 Click data from job-room.ch

I have data on all the clicks from registered unemployed in the window 06-06-2020 - 30-06-2021, obtained from job-room.ch. I can link jobseekers' clicks on job postings to their unemployment records. For every click, I know the timestamp of the click and a person identifier allowing me to link the click to the unemployment register entry. I further know an job posting identifier which allows me retrieve the content of the job posting from the publicly available API of the platform, even for job postings that are not online anymore at the time of the API request. I scrape the API, sending a request for every ad-identifier and obtaining the posting's content for every posting listed on the platform during the click recording window.

89% of the job posting records from the API directly include the municipality of a job. For the rest, I exploit the postcode of the firm using a crosswalk provided by the Swiss Federal Statistical Office to match the postcodes to the municipalities. For postcodes that cannot be matched this way, I take the the municipality with the highest overlap in buildings with the postcode, this is an information provided in the crosswalk. I end up being able to assign a municipality to 93% of job postings. I map the municipalities to the 101 small labor market locations defined by the Swiss Federal Statistical Office using the official crosswalk.

The occupation of a job is extracted from the job posting by the platform provider and reported in the API response. The classification of the occupation extracted is the same, internal, classification as used in the unmeployment records. I hence use the crosswalk from the unemployment records data to match the occupations to the ISCO. A job posting can be matched to more than one internal occupation. However, only 3% of the postings are matched to more than one ISCO occupation (on the most granular level), and no posting is matched to more than 3 different ISCO occupations. In those rare cases, I randomly pick an occupation out of the matched ones to simplify the estimation by having a unique occupation per job. The hours offered in a job posting are extracted from the posting by the provider of job-room.ch. Job postings provide a single number or a range of the hours worked, indicated as a percentage of a full-time job (100% corresponds to 40-42 hours per week). I classify a a job posting as being part-time if the lowest value of the stated workload range is 80% or less of a regular full-time workload. The API response further includes the name of the posting company as a free-text field, as it is written by the company posting the job.

2.5 Sample Restrictions and Descriptives

I use two samples of jobseekers from the unemployment register. The main estimation of the effect of job openings on unemployment exit is based on a sample of all spells of registered unemployed starting between January 2019 and June 2021. The administrative data contains 761,331 such unemployment spells. In the subsequent data cleaning process, I apply several exclusion criteria. Spells corresponding to individuals below 18 at registration and those lacking data on education level or municipality of residence are excluded, resulting in 748,485 spells. 510 spells (0.07%) are excluded because they show a deregristration date that is earlier than the registration date, most likely reporting errors. Additionally, I exclude spells where individuals find employment at the same company as their previous job, a potential indicator of temporary layoffs prominent in sectors such as construction D. Liechti et al. (2020). This reduces the dataset to 700,828 spells. Jobseekers can have more than one unemployment spell, my sample of 700,828 spells corresponds to 578,881 unique individuals.

The estimation of the job consideration logit model is based on the subset of the registered jobseekers who use the job-room for their job search. I use the clicks by all jobseekers who click on at least five job postings. The click data is recorded in the window 06-06-2020 - 30-06-2021. I exclude the first and last month of the data, as I will aggregate clicks on monthly level and I do not have the full month of data for these months. The final click sample, thus is 2020-07-01 to 2021-05-31. In order to be able to track a jobseeker's behaviour from the beginning of the spell, I only use clicks made by jobseekers who start their spell within that period. During that period, my main sample contains 258,745 spells. In 57,813 (22.3%) of them, five or more clicks were recorded. There are very few jobseekers with more than one spell in that sample, the 57,813 spells correspond to 56,662 people. On the click level, I address the issue of repeated clicks on the same posting, only

Table 1: Characteristics of unemployment spells sample

	All spells (N = 700 828)			Clickers (N = 57 813)		
	Mean	Min	Max	Mean	Min	Max
Female	0.46	0.00	1.00	0.52	0.00	1.00
Has children	0.33	0.00	1.00	0.35	0.00	1.00
Female x has children	0.15	0.00	1.00	0.19	0.00	1.00
Age (at registration)	38.21	18.00	78.97	39.23	18.02	64.68
Primary education	0.26	0.00	1.00	0.20	0.00	1.00
Secondary or vocational educ.	0.49	0.00	1.00	0.53	0.00	1.00
University education	0.16	0.00	1.00	0.21	0.00	1.00
Swiss	0.54	0.00	1.00	0.58	0.00	1.00
> 3 years tenure in last job	0.64	0.00	1.00	0.66	0.00	1.00
Spell duration (months)	6.64	0.03	40.13	6.92	0.03	23.30

This table presents the characteristics of unemployment spells within our sample, covering two distinct groups: all unemployment spells from January 2019 to June 2021 and a subset of these spells for individuals starting their spells in the click recording period July 2020 and May 2021 with 5 or more clicks on job postings on job-room.ch.

clicks on the same advertisement that occur on distinct days are retained in the dataset.[7]

Table 1 shows characteristics of the selected sample and also compares them to the characteristics of the population of registered unemployed. The average age at registration in the click sample is 39.2 years, slightly higher than the 38.2 years observed in the broader population. The click sample contains 52% females, compared to 46% in the entire population. In terms of educational background, the large part of the sample has completed secondary or vocational education, the educational attainment in the click sample is slightly higher compared to all unemployed. The average unemployment spell duration of completed spells in the click sample is 6.92 months. In the broader population, this figure is and 6.64 months.

2.6 Job openings

To measure job openings, I use a dataset containing the near-universe of online vacancies in Switzerland, scraped from the web by X28, a human resources company. The dataset contains the date of posting and the date of removal of the vacancy, allowing me to calculate the inflow of vacancies but also the stock of vacancies at any point in time (unlike other data providers, like Lightcast which measures only the inflow). It also contains the occupation of the job positing, classified according to the same internal classification as the unemployment records. I map the occupations to ISCO using the crosswalk provided by the unemployment records. The dataset also contains the company

[7]Most of the repeated clicks within a day are from the same minute, suggesting that they are attributable to technical issues rather than specific search behavior.

posting the vacancy, the job title, the location of the job, the hours, and the job description. Moreover, it contains a classification of the company into recruitment agencies and other companies. The dataset contains 2.44 million vacancies posted between 01-01-2020 and 31-12-2021. Colella et al. (2024) provide an in-depth overview of the data and show the representativeness of the data for the Swiss labor market.

In 92% of cases, the vacancies include location information at the postcode level. I match these postcodes to the labor market locations by intersecting their spatial representations and assigning each postcode the labor market location it overlaps the most. The map shapefiles are obtained from the Swiss Post and the SFSO, respectively. For postcodes that cannot be matched this way, I progressively truncate their digits and assign the mode of the location at each truncated level, ensuring that all postcodes are mapped to a location. The stock of vacancies in a certain submarket is computed as the difference in the cumulative number of vacancies published and the cumulative number of vacancies taken off the internet.

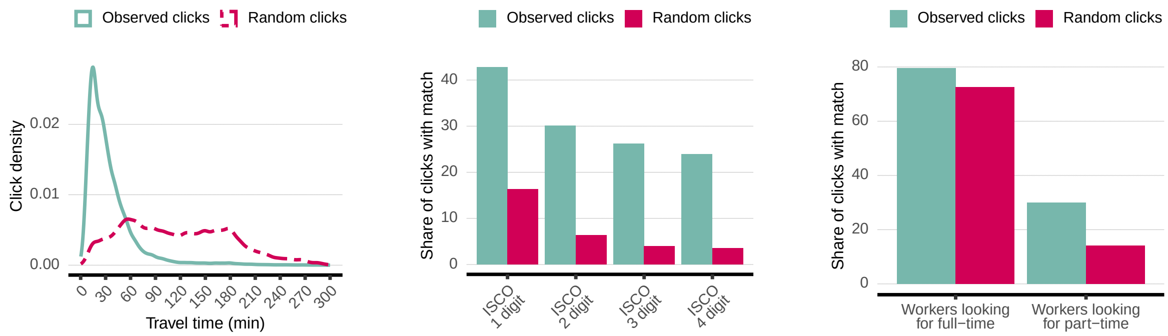
2.7 Descriptive evidence of targeted click behaviour

A descriptive analysis of the job postings clicked indicates that jobseekers take a targeted approach. This is reassuring because it suggests that clicks contain meaningful information about jobseeker preferences and constraints, and can serve as a proxy for job consideration. To assess the extent of targeted click behavior, I construct a random counterfactual: for each click, I sample a random posting from the distribution of clicked postings. This sampling procedure ensures that the number of clicks per posting and click per jobseeker in the random counterfactual matches the actual data.

Figure 3a depicts the travel between a job and the jobseeker's home. Jobseekers tend to click on postings much closer to their hometown than if they were selecting jobs at random. The median travel distance between the municipality of residence and the job's municipality is 26 minutes. The number of clicks on jobs further away declines sharply. This contrasts with the random counterfactual which suggests that most jobs lie within a distance range of 45 minutes and 3 hours.

Figure 3b examines the extent to which the occupation of a clicked job posting matches the jobseeker's past employment. 43% of clicks go towards postings with the same ISCO-08 1-digit code as the occupation of the last job before unemployment. With a more granulary definition of an occupation the share is even lower. This figure is relatively low, indicating that factors other than occupation play a crucial role in shaping job consideration. However, the share is substantially higher than what would be expected under random clicking. In a random scenario, a jobseeker would only click on a job matching the ISCO 4-digit code of their past occupation in 4% of cases.

Figure 3: Comparison of clicked jobs to a random counterfactual.



(a) Distance between job and home

(b) Job's occupation matches jobseeker's last occupation

(c) Hours worked match preference

The figure compares actual jobseeker clicks with a constructed random counterfactual. For each actual click, a random posting was sampled from the distribution of all clicked postings, matching the number of clicks per posting and per jobseeker found in the observed data. The analysis includes all clicks from 57,813 jobseekers who clicked on a minimum of five job postings from July 1, 2020, to May 31, 2021. Source: Data derived from job-room.ch, administrative records, and own calculations.

In contrast, the actual data shows this probability to be six times higher, at 24%. Klaeui et al. (2023) investigate the occupational mobility of jobseekers on job-room.ch woth the same data in more detail.

Lastly, Figure 3c assesses the alignment between the hours worked in a job posting and the jobseeker's preference for working hours. Jobseekers are more likely to click on postings that match their preferred working hours than if they were choosing randomly. For those seeking full-time employment (typically 36 or more hours per week), 80% of their clicks are on full-time job postings. Conversely, those seeking part-time employment click on postings that match their stated preferences 30% of the time, which is almost double the rate of 16% that would be expected if they were clicking randomly.

3 Estimation of job consideration

Utilizing discrete choice models to analyze decision-making processes becomes notably challenging as the number of options available to the decision-maker increases. Workers face a vast array of 70'000 to 110'000 jobs on the portal at any point in time. This increases the computational complexity of the problem. Furthermore, it is likely that the idiosyncratic terms in the utility are correlated across jobs, for example, within a location or an occupation. To reduce the complexity and alleviate concerns about the independence of irrelevant alternatives assumption, I apply a nested logit model similar to the one employed by Azar, Berry, & Marinescu (2022). The authors use application data to estimate preferences over jobs and, eventually, employer market power.

I split the labour market into granular submarkets. I define a submarket of the labour submarket as a location × occupation × hours worked combination. In the definition of the submarkets, I employ a more granular split than Azar, Berry, & Marinescu (2022). Similar to Manning & Petrongolo (2017)'s model of search across geographic labor markets[8], my aim is to model jobseekers' consideration as a mixture of submarkets. Therefore, I use a definition of a submarket that is small enough not to capture the full search scope of a worker: ISCO 3-digit occupation (the second most granular level), full-time or part-time status and location. The location is defined as sub-units of commuting zones, segmenting commuting zones into 2 to 12 granular locations. In my dataset, there are 119 different occupations, 101 locations, and 2 workload categories.

The nested logit can be described as follows: At the top-level, jobseekers decide which submarkets (m) to consider. This decision is influenced by the occupation, location and hours worked of the submarket and the jobseeker's preferences. Given the choice of a submarket, the jobseeker then chooses a specific job (j) within that submarket. This choice is based on the attributes of the individual jobs, including how well they match the jobseeker's preferences and requirements. The two decisions are not assumed to be independent but they are linked through a specific functional form, stemming from the set up of the nested logit model (Train, 2003).

The two-level set-up of the model also reflects some general patterns in online job search: In almost all internet job search processes, the jobseeker first has to apply some filter criteria. This could be entering a specialized job portal or also entering one or more search criteria after entering a general job portal, as it is the case with job-room.ch. Frequently used filter criteria are the occupation and the location of a job. Typically, these criteria narrow down the number of available jobs to a small portion of the overall job market. The job seeker is then presented with a list of jobs that meet the filter criteria and can make further selections.

Jobseekers typically engage with multiple search channels simultaneously, with the mode in Switzerland being 9 parallel search channels (D. Liechti et al., 2020). Therefore, the clicks observed for each jobseeker on the platform may not accurately reflect the extensive margin of job search. I account for this by focusing on the intensive margin and conditioning my analysis on a click on the platform.

[8] Manning & Petrongolo (2017)structurally model jobseekers' distributing their application over small geographic units (wards), in a directed job search framework where the number of applications depends on the ratio of vacancies to jobseekers per ward and a measure of commuting costs

3.1 Basic assumptions

The utility a jobseeker gets from clicking on a job is a function of the job's value and of the match between the jobseeker and the job. The job's value encapsulates all aspects of the job that are assumed to be constant over jobseekers, for example the wage level.[9]. The match between the jobseeker and the job is parametrized as depending on three dimensions: the commuting time between the jobseeker and the job, whether the occupation of the job matches the jobseeker's last occupational experience and whether the hours of the job match the jobseeker's workload preference. Any other match components are captured by an idiosyncratic component, $\varepsilon_i j$, that is allowed to vary over jobseeker-job combinations and is assumed to be exogenous to the other parts of the utility. Further, the utility is allowed to depend on the age of the vacancy at the time the job-seeker sees it. Older vacancies might seem less attractive to jobseekers, or the jobseeker might assume it is more likely to be already filled. Further, they might appear in a lower position in the results list if there are a lot of results matching a jobseeker's search. The search criteria entered by the jobseekers and the resulting list of job postings are not reported in the data.

$$u_{ijt} = \delta_j + \beta^d \log(\text{commute}_{ij}) + \beta^o O_{ij} + \beta^h H_{ij} + \gamma \log(\text{vacancy\_age}_{jt}) + \varepsilon_{ij} \tag{1}$$

In detail, to measure the commuting time, I use the travel time by car between the jobseeker's residence and the job's location, $log(comm_{ij}) = log(CommuteTime_{ij})$. The alignment between the jobseeker's previous occupation and the occupation stated in the job posting is assessed using dummies whether the ISCO codes match, $O_{ij} = \mathbb{1}\,[\text{ISCO-08}_{\text{last job i}} = \text{ISCO-08}_j]$. I employ two dummies, one at the broader two-digit level and one at the more granular three-digit. The third dimension is the compatibility of the job's workload with the workload hours preferred by the jobseeker. I compare the number of hours a jobseeker is looking for, indicated in their unemployment register record, with the hours offered in the job posting. A jobseeker and a job posting are classified as matching if the jobseeker is seeking a part-time job and the job posting offers part-time hours, or if the jobseeker is seeking a full-time job and the job posting offers full-time hours, $H_{ij} = \mathbb{1}\,[\text{Part-time preference}_i = \text{Part-time}_j]$. The vacancy age is the (log) number of days the vacancy has been online at the time of the click.

δ_j represents the job fixed effect. This parameter is flexibly estimated to capture all the characteristics of a job posting, observable or unobservable, that influence the utility of all jobseekers

[9]This study investigates clicks on jobs, and the wage level is almost never posted in Switzerland. Thus, the job value captures all information related to the wage level such as the exact job title or other hints that jobseekers can infer from the preview of the job (see Figure 2 for examples of this preview)

in the same way. One of the critical aspects captured by δ_j is the jobseekers' beliefs about wages. In Switzerland, it is notably rare for job postings to explicitly mention salaries.[10].

3.2 Bottom level logit: Choice between jobs within a submarket

Conditional on clicking in submarket m in month t, the probability that individual i clicks on a job j is a function of a job fixed effect δ_j and the number of days the vacancy has been online already at the time of the jobseeker click.

An attractive feature of the nested logit model is that it allows to estimate the bottom and the top logits separately (Azar, Berry, & Marinescu, 2022; Train, 2003). The bottom-level model is conditional on clicking in a submarket, and hence, the choice-set for every click is the number of other jobs available in the clicked submarket in the month of the click. If the model were to be estimated without this separation, for every click, the choice set would be any other job in the economy, which would make the estimation unfeasible. To estimate the logit model, I exploit the equivalence between the likelihood functions of the Poisson and the multinomial logit model. A Poisson model is less computationally demanding and estimates the same coefficients. This procedure has been used in the literature (Baker, 1994; Guimaraes, 2004; Schmidheiny & Brülhart, 2011; Taddy, 2015; Hirsch et al., 2021). The dataset is in a long format, where one row is one person-job-month combination and the dependent variable is a binary variable indicating whether the job was clicked on. For every person, month, and submarket, there is one observation per job that was available in the submarket in the month. I then stack all these observations for all person-month-clicked submarket combinations and include a person-month-submarket fixed effect (*"choice situation fixed effect"*) ensures the equivalence between the Poisson and the logit model. A further advantage of the Poisson model is that I don't have to estimate one model per person and click, but the estimator allows me to aggregate over all of a jobseeker's clicks in a submarket month. This allows me to reduce the number of observations to one observation per jobseeker and job in a submarket-month[11]. I estimate the high-dimensional fixed effects Poisson model using the *fixest* package in R (Bergé, 2018).

The aggregation at the monthly level comes at the cost that the day of the click and hence

[10] `https://jobs-mit-gehaltsangabe.ch/` is a portal by a human resource company showing only vacancy postings with posted wages in Switzerland, comparing their total numbers of openings in the database of the same company indicates that only around 1% of job postings actually contain wage information.

[11] Studies using the Poisson transformation usually apply the Poisson estimator to a setting where there is one choice per person. In those cases, the choice situation fixed effect absorbs the inclusive value of the decision maker's choice set, ensuring equivalence to the multinomial logit model. In my setting, I sum over all the clicks jobs a jobseeker makes in a submarket month. In this case, the choice situation fixed effect additionally also absorbs the total number of clicks done by the jobseeker in the submarket-month.

the age of the vacancies is not properly defined anymore. I approximate the age of the vacancy by taking the age on the day of the jobseeker's first click in the month. If a vacancy was not online yet on that day, I take the first day with a click after the vacancy was created. If, in a given month, all of a jobseeker's activity on the platform took place before the vacancy was created, I exclude this vacancy from the choice set of the jobseeker in that month.

To make the model estimable, I have to make some restrictions on the data. For every submarket-month combination, I take the biggest connected set of jobseekers and jobs. This leaves me with 73.1% of the jobs and 99.7% of the jobseekers. Further, in order to be able to estimate job fixed effects within a submarket, I only keep submarket months with at least 2 vacancy postings. Submarkets can be very granular, thus this restriction excludes a big share of 54.7% of submarket-month combinations. However, those are submarkets with very few jobs: only 0.8% of jobseeker-job combinations are excluded. Next, I exclude months in which all jobseekers click on all jobs since that would prohibit any estimation of the job fixed effects. This happens in 5% of the submarket months but only excludes 0.1% of jobseeker-job combinations. I exclude all jobseeker-job combinations in a month if the job was not online yet at the last point in time the jobseeker clicks in the month. After these restrictions, there are 56,847 spells left from the original sample of 57,813. I estimate the within-submarket choice for 35521 submarket months and 7464 unique submarkets. In the average submarket, a jobseeker faces a choice of 22 jobs per month; this number ranges from 1 to 381 jobs, the median is 11. Conditional on at least one click in a submarket month, the mean number of clicks per jobseeker in the submarket is 2; this number ranges from 1 to 12 clicks in the 99th percentile, and 189 clicks at the maximum. A job is, on average, clicked on 8 times per month by jobseekers in my sample. This number ranges from 1 to 371; 99% of the ads are clicked on less than 64 times per month.

3.3 Top level logit: Choice across submarkets

The probability of a jobseeker i clicking on a job in submarket m is represented by the multinomial choice equation 2[12]:

$$P\left(\text{i clicks in submarket m} \mid \text{click}\right) = \frac{e^{\beta^d log(\text{comm}_{im}) + \beta^o O_{im} + \beta^h H_{im} + \delta_m + \lambda I_{mt}}}{\sum_{n=1}^{M} e^{\beta^d log(\text{comm}_{in}) + \beta^o O_{in} + \beta^h H_{in} + \delta_n + \lambda I_{nt}}} \tag{2}$$

[12] Azar, Berry, & Marinescu (2022) estimate the top-level choice using a binomial logit model on whether a jobseeker applied in a submarket in a month. This is a form of including the extensive margin of how much a person applies into the model. As outlined above, I condition my analysis on making a click on the platform. This decision is reflected in the top-level logit only including months with at least one click and taking the form of a multinomial logit model.

Apart from the 3 dimensions of match between the jobseeker and the jobs in the submarket, the model also includes a submarket-specific constant, δ_m. Azar, Berry, & Marinescu (2022) show that this constant can be interpreted as the job-specific constant of a reference job in every submarket. The top-level model also contains the inclusive value (I_{imt}), which links the two levels of decision-making. It is defined as a sum over all jobs, k, that are in submarket m at time t. This set of jobs is denoted as $\mathcal{J}_{mt}$.

$$I_{mt} = \log \sum_{k \in \mathcal{J}_m t} \exp\left(\delta_k + \gamma \text{vacancy\_age}_{kt}\right) \tag{3}$$

This value represents the log-sum of exponentiated utilities of the jobs, capturing the attractiveness of the submarket to the jobseeker at time t, relative to the submarket-fixed effect δ_m. The parameter λ in Equation 2 measures the influence of the inclusive value on the submarket choice, reflecting the degree of correlation within submarkets. A lower λ indicates stronger correlation of the utilities among jobs within the same submarket. A value of $\lambda = 1$ would indicate that the jobs within a submarket are as dissimilar in utility as jobs across submarkets and the model would collapse to a standard multinomial logit model. On the other side, $\lambda = 0$ would indicate that the variables included in the top nest – the match indicators and the submarket-specific constants – fully capture the utility of a job and that the jobs within a submarket are perfect substitutes. The coefficient on the inclusive value is identified through variations in the number of available jobs in a submarket across different months, and, additionally, through within-month variation in the age of vacancies. This within-month variation arises because different jobseekers access the job-room on different days, leading to differences in the set of job vacancies they encounter, both in terms of jobs in the set and the age of the vacancies in the set.

The same submarket presents varying commuting times and degrees of occupational match for different jobseekers. This variability allows me to disentangle the overall utility derived from submarket characteristics, encapsulated by the submarket-specific constant, from the utility associated with specific job attributes, such as the match indicators for occupation and hours worked.

For the estimation, I only use clicks made in the first three months of a spell. This is done to reduce the number of observations and to reduce potential effects of the prolonged spell duration on the jobseeker's search behavior[13]. This restriction excludes spells containing only clicks after

[13] An estimation using full spell duration yields very similar results. For the bottom-level analysis, I do not impose the restriction to the initial three months of a spell, opting instead to utilize the full duration of unemployment records. This decision is motivated by the desire to maximize the number of observations available for the analysis, which is crucial due to the connected set property of the data. Additionally, the focus on specific targeting within occupation categories and commuting time distances is less susceptible to variations over the duration of a spell, suggesting that the patterns of jobseeker behavior in these respects remain consistent over time.

Table 2: Estimates of job consideration using click data from an online job portal

	Bottom level	Top level	
	(1)	(2)	(3)
Dependent Var.:	N clicks	N clicks	N clicks
log(Vacancy age)	-0.5222*** (0.0031)		
log(Commuting time)		-2.541*** (0.0097)	-2.541*** (0.0097)
Match in 2-digit occupation		0.7827*** (0.0211)	0.7837*** (0.0210)
Match in 3-digit occupation		1.742*** (0.0241)	1.739*** (0.0240)
Match in hours		0.6257*** (0.0120)	0.6257*** (0.0119)
Inclusive value		0.2550*** (0.0032)	
Vacancy posting	Yes	No	No
Spell x month x submarket	Yes	No	No
Spell x month	No	Yes	Yes
Submarket	No	Yes	Yes
Observations	29,477,086	423,358,495	423,358,495
Pseudo R2	0.28361	0.48016	0.47852
N spells	56,134	53,617	53,617
N clicks	2,584,852	1,966,133	1,966,133
Mean count	0.0877	0.0046	0.0046

Estimates from fixed-effects Poisson regression on expanded data. The bottom-level logit is estimated on repeated choice situations where a jobseeker, conditional on being active in a submarket in a month, chooses which job to click on. The data contains one observation for every jobseeker–month-submarket-job combination where the dependent variable is the number of clicks by the person on the job. The top-level logit is estimated on an expanded jobseeker-month panel containing an observation for every jobseeker–month-submarket triplet and the dependent variable is the number of clicks by the person on the submarket in the given month. The model is conditional on clicking and only includes jobseeker-month combinations with at least one click. The analysis uses data from job-room.ch, covering clicks between July 2020 and May 2021. The sample includes all registered jobseekers who began their unemployment spell within the sample period and recorded at least five clicks on the platform. Standard errors are clustered by jobseeker spell. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

the first 3 months and leaves us with a sample of 54021 spells. During the initial three months of their unemployment spell, jobseekers engage with a diverse range of submarkets, clicking on an average of 6 submarkets each month. This activity spans a wide spectrum, with the scope of clicks per month extending from 1 submarket to 31 submarkets at the 99th percentile; the maximum being 330.

3.4 Results from the nested logit model

The results from the bottom-level logit are shown in Column (1). Conditional on clicking in a submarket, the elasticity of the number of clicks on a job with respect to the days the vacancy was online at the time the jobseeker is active is -0.445; At the median vacancy age of 7 days, the estimated elasticity implies a decrease of the conditional clicking probability of 0.66 percentage points (7.5%) when the vacancy gets one day older[14]. The main output from the bottom-level regression is a set of job-specific constants, which indicate the part of the utility of a job that is constant across jobseekers, such as for instance the wage[15]. Those values represent the differences in jobs within a submarket; they can be interpreted relative to a reference utility level in the submarket. On average, a very popular job within a submarket (the 90th percentile in job-specific utility) is 9.2 times more likely to be clicked than a not-so-popular job (10th percentile within the market).

Column (2) shows the results from the top-level model of the nested logit. My estimates show a high inclination to consider jobs close to home: the probability of clicking on a job 30 minutes away is only half the probability of clicking on a job 15 minutes away. Comparing this to the deterrence of distance in applications estimated by Marinescu & Rathelot (2018) on US data suggests that consideration is less affected by distance than applications. They find that the application likelihood decreases by 65% for a similar increase in distance.

Regarding the occupational match, my results reveal that a match within the more specific three-digit occupational category is significantly more crucial than a broader match at the two-digit level for job consideration. Specifically, a jobseeker is only 18% as likely to consider a job with a broad occupational match compared to a job with a match in 3-digit occupation. An occupational match at the three-digit level provides the same increase in utility of clicking on a job posting as a 63% reduction in the commuting time or shortening a 26-minute commute to just 10 minutes.

Finding a job that matches the individual's preferred workload is less important compared to the occupational match, it has the same effect on click utility as reducing the commute by 22%, for instance cutting a 26-minute journey to 21 minutes. In terms of job submarket attractiveness, the difference between a job in a highly popular submarket (90th percentile) and one in a less sought-after submarket (10th percentile) equates to a 63% decrease in the commute.

On the other side, the disparity in appeal between a very popular job and a less popular job within the same submarket only amounts to a 12% decrease in commuting time, or a reduction from 26 minutes to 23 minutes[16]. Moreover, the duration for which a vacancy has been advertised at the time of the click plays a significant role; a vacancy moving from being online for 29 days (90th

[14]Abstracting from very few cases of a person clicking on a job twice in a month, the mean count in the bottom-level dataset can be interpreted as a conditional clicking probability of 8.8%.

[15]Since in Switzerland it is very rare to post a wage on a vacancy posting, the job specific constants rather represent a wage belief based on observables such as the firm name and the jobtitle. These information are visible before clicking on the posting.

[16]The estimates from the bottom level logit model can be translated to the utility scale of the top level logit by multiplying them with the inclusive value coefficient.

percentile) to just 1 day (10th percentile) is valued similarly to a 16% decrease in commute distance. These findings highlight the filtering nature of the job-clicking process: Although jobseekers do not only click on jobs in one occupation or location, the vast majority of jobs are still excluded from consideration on the basis of occupation and location. Jobseekers still make decisions between jobs within occupations, but these are less important.

Column (3) shows the coefficients from an estimation without accounting for the inclusive value of the bottom nests. This specification can be interpreted as a simple Poisson regression on clicks aggregated on the submarket level[17]. Comparing Columns (3) and (2) suggests that the results do not crucially depend on the nested logit structure. the inclusive value allows us to compare the coefficients from this That the results don't change indicates that the inclusive value of a submarket not systematically correlate with the commuting distance or the other match indicators. Intuitively, the value of being able to choose the best job within a submarket, on average, does not depend on how "distant" this submarket is.

Figure 9 in the Appendix compares results for different functional forms of the commuting distance. It shows that the logarithm of the commuting time matches the results from a non-parametric approach based on indicator variables for 10-minute bins well. A linear form underestimates the decrease in utility for close-by jobs and overestimates the decrease for away jobs.

4 Heterogeneity in job consideration

For each individual, my dataset captures a multitude of decisions, with each jobseeker clicking on several jobs. I use this information in the data to estimate individualized coefficients. Specifically, I estimate the heterogeneity in the coefficients on commuting distance, occupational match and workload match across a spectrum of nine personal characteristics: gender; a dummy variable for having children; the interaction of gender and children; age groups; a dummy for non-Swiss passport holders; education categories; and a dummy for 3 or more years experience in the last occupation[18].

Incorporating the heterogeneity across personal characteristics leads to the following amended functional form of the top logit model.

$$P\left(\text{i clicks in submarket m} \mid \text{click}\right) = \frac{e^{\beta_i^d log(\text{comm}_{im}) + \beta_i^o O_{im} + \beta_i^h H_{im} + \delta_m + \lambda I_{mt}}}{\sum_{n=1}^{M} e^{\beta_i^d log(\text{comm}_{in}) + \beta_i^o O_{in} + \beta_i^h H_{in} + \delta_n + \lambda I_{nt}}} \tag{4}$$

[17]This regression is very similar to the two-way fixed effects version of the main Poisson regression in Marinescu & Rathelot (2018) estimating the effect of distance on applications.

[18]In theory, the multitude of clicks per individual could enable the estimation of individual-specific coefficients. To maintain my estimation's tractability and enable out-of-sample predictions of the estimated consideration probabilities, I opt for a more generalized approach.

where the vector of the 'individual' coefficients $\beta_i = (\beta_i^d, \beta_i^o, \beta_i^h)'$ depends on the personal characteristics:

$$\beta_i = \beta + \beta_1 \mathbb{1}\{X_{i1} = 1\} + \beta_2 \mathbb{1}\{X_{i2} = 1\} + \ldots + \beta_9 \mathbb{1}\{X_{i9} = 1\} \tag{5}$$

This analysis allows me to answer interesting questions, for instance: do women put a higher weight on commuting time when deciding which jobs to consider? Do jobseekers with a child at home restrict their consideration more to jobs where the hours worked match their stated preferences? Furthermore, in Section 5, I will use the predictions from the consideration model to investigate the effect of job openings interactied with how likely an individual is to consider the job opening. Allowing for heterogeneity in the job consideration model will enable me to make this prediction not only based on a jobseeker's occupation and location but also their personal characteristics. This allows me to go beyond the existing literature which usually assumes that all people within the same cell (for instance location, occupation or the interaction) consider the same jobs.

This model will be used to predict the probability of how likely an individual is to consider a new job opening, given the openings' submarket. Given the model's use for prediction, overfitting is a concern, especially for the large set of, potentially noisily estimated, submarket-specific constants. I impose a slightly more parametric form onto the submarket-specific constants and constrain them to be a function of the location of the submarket, the 3-digit occupation of the submarket, the full-time-indicator as well as the interaction between the broad occupation (2-dig) and the commuting zone (which is broader than the location) and the interaction of the broad occupation (2-digits) with the full-time-indicator. Moreover, as described in Section 5.1, I will apply Empirical Bayesian shrinkage to the estimates.

The heterogeneous model estimates a large set of coefficients and interactions. Additionally, the Bayesian shrinkage approach I apply necessitates the estimation of a standard error for each parameter. This has the consequence that the fixed effects for occupation and location, along with their interactions, cannot be absorbed through a within transformation as performed in the homogeneous effects model from Section 3. This large increase in dimensionality leads to a prohibitive demand of computation resources and I cannot estimate the model on the full sample. Consequently, for each click observed in the data, I adopt a strategy of randomly sampling 30 alternatives among the not-clicked markets. This method of sampling alternatives is a well-established practice in discrete choice model applications (see e.g. Train et al., 1987; Train, 2003). To account for the fact that the data is aggregated at the person-month level, I sample 30 alternatives multiplied by the total number of clicks made by the jobseeker within that month. Sampling is conducted with replacement to account for the repeated selection of alternatives within a jobseeker's monthly activity. As in Train et al. (1987), the sampling probability is proportional to the number of clicks in the nest [19]. I estimate the model on a "training" sample of 60% of the sample of clickers.

4.1 Results: Heterogeneous consideration

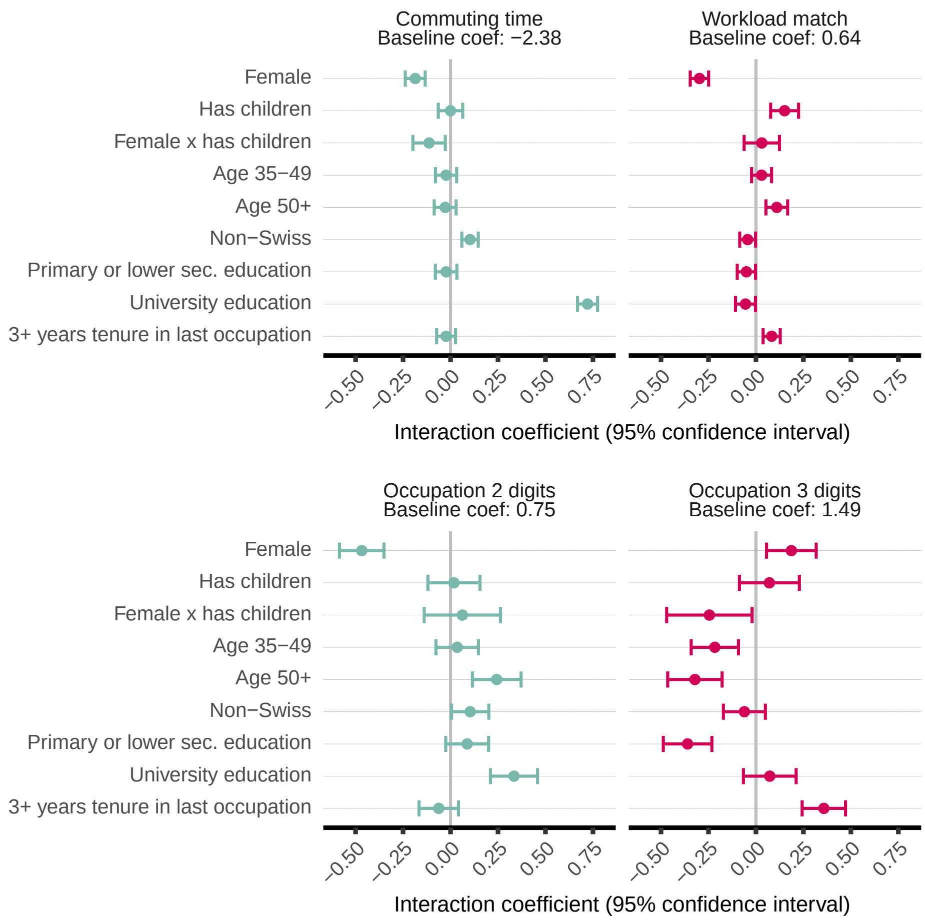
Figure 4 shows how the coefficient of the four match indicators vary with individual characteristics.

Gender and children. For commuting distance, female jobseekers exhibit a stronger deterrent effect against commuting, which becomes even more reinforced for those with children, indicating a 13% more negative weight on commuting time compared to the baseline coefficient of 2.38, presumably reflecting the role of child-care obligations as a constraint in job search. Having children only affects the weight on the commute for women, not for men. A lower coefficient on commuting for females, ceteris paribus, means that females value the commuting aspect more compared to the other aspects, including the wage beliefs captured in the job-specific constant. This finding is in line with Le Barbanchon et al. (2021) who find that women are more willing to trade off a short commute against a higher wage than men in the range of jobs they state that they are willing to work in in a survey with the unemployment services. It is also in line with Fluchtmann et al. (2022) and Philippe & Skandalis (2023) who find similar results looking at application data and who also find that the gender gap in search for jobs further away from home is larger for women with children.

Female jobseekers value workload match less in their consideration decision, suggesting that other factors outweigh workload compatibility. However, jobseekers with children value workload alignment more than those without children. The effect of children on the weight of workload match is not differential by gender. The negative interaction for female jobseekers with the coefficient on match in 2-digit occupation (-0.4678) indicates that broad occupational alignment is much less critical or appealing for female jobseekers. This result that occupational match plays a smaller role for women in their consideration, adds an interesting dimension to the established findings about the gender difference in the trade-off between commute and wage: There seems to be another aspect to it, occupational flexibility. My results suggest that women compensate for the reduced geographical consideration scope by showing greater occupational flexibility. The positive interaction with the

[19] For the homogeneous coefficients-model, I can run the regression with the full sample. This is a good setting to show the convergence of the coefficients as soon as the number of randomly sampled alternatives becomes large. This exercise is shown in Appendix Figure 10.

Figure 4: Effect of personal characteristics on distance and match parameters.



Interaction coefficients from a fixed-effects Poisson regression on an expanded jobseeker-month panel containing an observation for every jobseeker–month-submarket triplet. The dependent variable is the number of clicks by the person on the submarket in the month. The analysis uses data from job-room.ch, covering clicks between July 2020 and May 2021. The sample includes a random 60% sample of all registered jobseekers who began their unemployment spell within the sample period and recorded at least five clicks on the platform. The sample comprises 32,236 spells, 22,466,892 spell-month-submarket combinations (=N obvservations) and 1,170,942 clicks. Standard errors are clustered by jobseeker spell. 95% confidence intervals shown.

coefficient on the match in 3-digit occupation (0.1866) for female jobseekers is small compared to the high baseline coefficient of 1.49, and for women with children, the cumulative difference is close to 0.

Age. Age, for the most part, does not significantly alter the baseline coefficients, relative to the reference group of young jobseekers (aged 18-34). Jobseekers aged 35 and above exhibit a slight but significantly lower valuation of precise occupational matches (as indicated by a negative interaction with "match in 3-digit occupation"). For older jobseekers (aged 50+), the overall effect of occupational match is similar to the broad population of jobseekers, however they seem to put a higher weight on the broad match and a lower weight on the more precise occupation match.

Migrants. Jobseekers without a Swiss passport display distinct preferences regarding commuting distance. The positive interaction coefficient suggests a slightly higher tolerance for longer commutes compared to Swiss nationals, the weight on commuting distance is 4% lower, ceteris paribus. This result is congruent with the finding that migrants are more mobile in moving for work, as found for Mexican-born workers in the US (Cadena & Kovak, 2016) and immigrants in Germany (Schündeln, 2014). Foreign nationals' valuation of occupational matches and workload alignment largely mirrors the baseline preferences, showing that, beyond commuting, their job consideration factors align closely with those of Swiss jobseekers.

Education. In the context of education, jobseekers with primary education and those with university degrees exhibit distinct patterns in job consideration compared to the reference group of individuals with secondary and vocational education. Jobseekers with primary education tend to show a lower emphasis on precise 3-digit occupational alignment (a 24% lower weight), potentially due to the broader nature of their job qualifications compared to the occupation-specific focus of secondary and vocational education. University-educated jobseekers demonstrate a higher tolerance for commuting (a 30% lower weight), potentially reflecting a feature of a more specialised labour market with jobs mainly located in bigger cities, which in turn are well connected in Switzerland. They also exhibit an increased focus for broad occupational matches (0.3343; +44%), suggesting that the high human capital is specific at the broad level, but at the more precise occupational level, there are no differences to secondary education.

Occupation-specific human capital. A feature of the unemployment register data is information on the occupational tenure of a jobseeker. Jobseekers with more than three years of occupation-specific experience have a higher valuation of precise occupational matches at the 3-digit level (+ 24%), potentially a reflection of accumulated occupation-specific human capital. This result is in line with the findings by Gathmann & Schönberg (2010) that the propensity to switch occupations declines with labour market experience. The responses to commuting distance and workload match do not show significant deviations from the baseline.

5 Interplay of job openings and consideration

This section connects an unemployed individual's probability of finding employment to the availability of jobs, categorizing the job openings based on how likely the jobseeker is to consider them.

5.1 Panel of job openings by predicted consideration

I construct a monthly panel of all jobseeker unemployment spells and an indicator of whether the jobseeker exits unemployment to a new job in the subsequent month. My estimates of consideration probabilities allow me to categorize job openings by how likely a jobseeker is to consider those jobs. To interact the job openings with the consideration, as a first step, I predict the consideration for each jobseeker and each submarket. The predicted consideration probability of submarket m for jobseeker i is

$$P_{im} = \frac{e^{\hat{\beta_i}^d log(\text{comm}_{im}) + \hat{\beta_i}^o O_{im} + \hat{\beta_i}^h H_{im} + \hat{\delta}_m + \hat{\lambda}\bar{I}_m}}{\sum_{n=1}^{M} e^{\hat{\beta_i}^d log(\text{comm}_{in}) + \hat{\beta_i}^o O_{in} + \hat{\beta_i}^h H_{in} + \hat{\delta}_n + \hat{\lambda}\bar{I}_n}} \tag{6}$$

where I used the model that estimates heterogeneous β across a range of 9 personal characteristics. Hence, $\hat{\beta}_i$, the vector of estimated coefficients on the commuting distance, the two occupational match dummies, and the hours match dummy, for jobseeker i takes the following form.

$$\hat{\beta}_i = \hat{\beta} + \hat{\beta}_1 \mathbb{1}\{X_{i1} = 1\} + \hat{\beta}_2 \mathbb{1}\{X_{i2} = 1\} + \ldots + \hat{\beta}_9 \mathbb{1}\{X_{i9} = 1\} \tag{7}$$

Apart from the 'individualized' $\hat{\beta}_i$, the prediction uses the submarket-specific constants, $\hat{\delta}_m$ as an input, those are constant across jobseekers and capture all the parts of the utility that is the same for everyone, such as for example the typical wage of the submarket. Those submarket fixed effects might be estimated noisily and distort the prediction. As outlined above, I address this issue by imposing a more parametric form restricting them to be a function of the location of the submarket, the granular, 3-digit occupation of the submarket, the full-time-indicator as well as the interaction between the broad occupation (2-dig) and the commuting zone (which is broader than the location) and the interaction of the broad occupation (2-digits) and the full-time-indicator.

Moreover, I apply Empirical Bayesian shrinkage to the fixed effects and shrink the components of the submarket fixed effects described above toward their mean. Using estimated fixed effects is a common problem in the teacher value-added literature in the economics of education and I follow Koedel et al. (2015) in the implementation of the shrinkage[20]. However, after the parametrization outlined, the components of the fixed effects are estimated precisely, and the shrinkage only has a small effect.

A potential concern is that jobseekers' consideration does not solely reflect their preferences or constraints but that jobseekers also target their consideration towards segments of the economy where there are a lot of jobs, thereby creating a mechanical relationship between consideration and job openings. The first step I undertake to mitigate this concern is to use time-constant consideration probabilities. The inclusive value is the channel through which the consideration predictions could vary over time and react to the current economic situation. If the arrival rate of job openings in a submarket increases, the inclusive value increases as well. This interdependence between the predicted consideration and job openings could lead to endogeneity in estimating how their interaction affects job finding. Therefore, I shut down this channel and use a time-constant value for the inclusive value of a submarket. Specifically, I use the average inclusive value of a market over all jobseekers and months for the prediction. Column (3) in top nest estimation, Table 2 shows that the coefficients on the other dimensions do not depend on having the inclusive value in the model. This is reassuring, indicating that shutting down the inclusive value channel in the prediction does not skew the prediction results.

Furthermore, to deal with potential bias arising from utilizing the same individuals for both the estimation of job consideration and the analysis of job openings' impact on job finding, I employ a "leave-out" estimator approach for job consideration. This involves dividing the sample of job-room users into two distinct subsets: a "training" sample for deriving the job consideration model and a "test" sample for conducting the regression analysis of job openings on job-finding outcomes. This division ensures that the individuals contributing to the estimation of the consideration coefficients are distinct from those included in the subsequent analysis of jobseeker behavior; the individuals used to predict $\hat{\beta}_k$ are not used in the jobseeker month panel.

Table 3 presents the predicted consideration probabilities for an example jobseeker, showing the top 10 submarkets with the highest consideration probabilities based on his personal characteristics, last occupation, location, and workload preference. The table shows that for the example jobseeker from Montreux, seeking full-time work as a construction laborer, the top 10 submarkets primarily include roles within and around the Montreux–Vevey area. The top-ranking submarket

[20]To correct the variance average fixed effects for the estimation error in its components I apply the correction factor used by Aaronson et al. (2007).

Table 3: Examples of a jobseeker's top 10 considered submarkets

Rank	$\hat{P}_{leave-out}$(consider m$\|X_i$)	Location	Commuting time	Occupation	Hours
1	1.46%	Montreux–Vevey	18 min	Construction labourers	Full-time
2	0.77%	Montreux–Vevey	18 min	Manufacturing labourers	Full-time
3	0.62%	Montreux–Vevey	18 min	Transport and storage labourers	Full-time
4	0.5%	Aigle	34 min	Construction labourers	Full-time
5	0.46%	Lausanne	32 min	Construction labourers	Full-time
6	0.45%	Monthey	40 min	Construction labourers	Full-time
7	0.44%	Montreux–Vevey	18 min	Manufacturing labourers	Part-time
8	0.43%	Montreux–Vevey	18 min	Rubber, plastic and paper products machine operators	Full-time
9	0.36%	Saanen–Château d'Oex	66 min	Construction labourers	Full-time
10	0.36%	Montreux–Vevey	18 min	Textile, fur and leather products machine operators	Full-time

For an example jobseeker, the table shows the 10 submarkets with the highest consideration probability given the jobseeker's personal characteristics, last occupation, location, and workload preference. The predictions are computed on a sample omitting the sample used for the estimation of the consideration probabilities.

for the jobseeker, has a consideration probability of 1.46%. This is approximately 110 times higher than the baseline chance of a random submarket selection, which stands at about 1/7500. The results notably highlight submarkets within and outside the jobseeker's residence in Montreux. The consideration probabilities for submarkets like Aigle or Lausanne are still about 35 times greater than the chance of a random selection. Beyond the jobseeker's last role in construction, there are distinct occupations with consideration probabilities vastly exceeding the baseline chance of a random submarket selection.

When looking at how similar these lists are over jobseekers, the results show substantial heterogeneity in consideration, even among people with the same last occupation and location. On average, two people with the same last occupation and same location share 5.97 of their 10 most considered submarkets. Additionally, the order is different, the average rank correlation of the first 10 submarkets of two jobseekers with the same last occupation and location is 0.17. When looking at the commonly used definition of a labor market by commuting zone and occupation (e.g used in Şahin et al., 2014; Herz & Van Rens, 2020; Azar et al., 2020; Azar, Marinescu, & Steinbaum, 2022), the average overlap in the ten most considered submarkets between two people in the same labor market is only 3.0, and the rank correlation 0.08.

Given the leave-out predictions of consideration probabilities for every individual in the panel and every submarket m, I merge the number of job openings to the panel. For every jobseeker, I rank all the submarkets by their predicted consideration probabilities. I then aggregate them into bins of the jobseeker's 1st to 10th most considered submarket, the 11th to 20th most considered markets, and so on. For every jobseeker and month, I aggregate the stock of vacancies for those bins and merge them to the panel.

The submarkets are based on a very granular level and not all the occupations in the click data are also represented in the vacancy data, leading to some submarkets with 0 vacancies over the whole sample period. Those zeroes are likely to stem from definition issues and don't have an economic meaning. I exclude jobseekers from the analysis who have more than 5 zero-only submarkets in their top 20. Note that I do not exclude submarkets or jobseekers for which the number of vacancies goes to 0 in some months but is positive in other time periods.

5.2 Baseline estimates

To assess the interplay between job openings and the consideration probability, I estimate the effect of job openings on a jobseeker's job finding probability using a discrete-time hazard model of unemployment exit.

$$Y_{it} = \gamma_1 V_{1-10,it} + \gamma_2 V_{11-20,it} + \ldots + \zeta_1 U_{1-10,it} + \zeta_2 U_{11-20,it} + \ldots + X_{it}\theta + \mu_t + \nu_{\tau(i,t)} + \varepsilon_{it} \quad (8)$$

In the specified model, Y_{it} indicates whether individual i leaves unemployment within the next month. The hazard is modelled as a function of job openings, V, the number of other unemployed, U, the elapsed unemployment duration τ and control variables, X. $V_{1-10,it}$ denotes the number of job openings at time t, in individual i's 1st to 10th most considered submarkets, ranked by their leave-out prediction from the consideration estimation. $V_{11-20,it}$, ..., capture the number of job openings in the 11th to 20th most considered submarkets, respectively. The coefficients γ_1, γ_2, ..., quantify the impact of job openings in these preferred submarkets on the likelihood of unemployment exit. If the effect of job openings is higher in more considered submarkets, one would expect $\gamma_1 > \gamma_2 > ....$ I use the rolling 3 months average of the stock of vacancies per submarket. The rationale for using such a long window is the lag between the search activity and unemployment exit to a job. This lag is sizeable and can be different for different jobs and people. Bassier et al. (2024) use the same click and administrative data as I do and show that the strongest effects of search activity on the probability of finding a job are found 2 to 3 months after the search activity.

$U_{1-10,it}$, $U_{11-20,it}$, ... represent the number of unemployed individuals within these same submarket preferences, with ζ_1, ζ_2, ..., measuring their respective influences on the unemployment exit probability [21].

[21] As seen in the previous parts of this study, jobseekers tend to consider several submarkets. When measuring the number of jobseekers, I account for this fact. I use a consideration-weighted measure of the number of jobseekers per

$\nu_{\tau(it)}$ is a fixed effect for the number of months elapsed since the individual started the unemployment spell $\tau(it)$, flexibly accounting for duration dependence in the job finding probability and the mix of long and short-term unemployed in the sample in any given month (Zuchuat et al., 2023). The time-fixed effect, μ_t, accounts for economy-wide fluctuations in job finding probabilities. X_{it} includes other covariates that may affect the exit probability. θ is a vector of coefficients. The first variables in X_{it} are a set of fixed effects for the last occupation of the jobseeker, the location of residence and for whether the jobseeker is looking for a part-time or full-time job. Further, I include an interaction between the occupation and the location and between the occupation and the part-time indicator. These variables capture differential job finding baseline probabilities for different types of jobs and different arrival rates of job openings for different types of jobs. Moreover, the specification includes a list of personal characteristics accounting for the influence of personal characteristics on the job finding probability. The list of personal characteristics used is the same as the characteristics used as an input for the prediction of the leave-out consideration probabilities: gender, a dummy variable for having children, the interaction of gender and children, age groups, a dummy for non-Swiss passport holders, education categories and a dummy for 3 or more years experience in the last occupation. Intuitively, the model compares the exit hazard of two people, with the same last occupation, the same location and the same part-time-preference. There are two sources of difference between the two people driving the identification, the first is that their spells start at different times and therefore, they face a different distribution of job openings. The time-fixed effect μ_t controls temporal variations in the job finding probability that uniformly affects all individuals in month t. The second source of variation is that, based on their personal characteristics, they consider a different combination of submarkets and these submarkets differ in the number of job openings. The estimation controls for all the personal characteristics used in computation of the job consideration. This conditioning isolates the effect of the interplay between the consideration and the job openings from personal characteristics jointly affecting the consideration scope and the job finding probability. The panel of jobseekers contains a lot of information

submarket.

$$U_{mt} = \sum_{i \in \mathcal{U}_t} \hat{P}_{leave-out}(\text{consider m}|X_i) \tag{9}$$

where $\mathcal{U}_t$ is the set of jobseekers registered as unemployed in month t. For every jobseeker, I use the leave-out prediction of how likely they are to search in a submarket given their personal characteristics, location, last occupation, and workload preferences. To account for the fact that the set of jobseeker used to estimate the consideration probabilities is omitted here, I scale up each U_{mt} with the ratio of the total amount of jobseekers to the amount of jobseekers not used for the training sample. This is a minor scaling, since only 60% of the jobseekers clicking more than 5 times on job-room is used for the estimation of the consideration model and the measure here is computed using all registered jobseekers. For computational reasons, if the consideration probability is in the bottom 25% for a jobseeker, I set it to 0. Intuitively, this restriction doubles as a crude correction for the fact that the nested logit model can't predict a probability of 0 to consider a market.

Table 4: Explaining job finding with job openings in most considered submarkets

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment
log(V in 1-10th submarket)	0.0056*** (0.0002)	0.0019*** (0.0003)	0.0023*** (0.0003)	0.0025*** (0.0003)	0.0021*** (0.0003)	0.0023*** (0.0003)
log(V in 11-20th submarket)	-0.0002 (0.0002)	-0.0013*** (0.0002)	0.0006** (0.0002)	0.0006** (0.0002)	0.0005** (0.0002)	0.0005** (0.0002)
log(V in 21-50th submarket)	-0.0052*** (0.0002)	-0.0046*** (0.0003)	-9.77e-5 (0.0003)	0.0004 (0.0004)	0.0005 (0.0004)	0.0005 (0.0003)
log(U in 1-10th submarket)				-0.0046*** (0.0010)	-0.0052*** (0.0010)	-0.0044*** (0.0010)
log(U in 11-20th submarket)				0.0042*** (0.0009)	0.0042*** (0.0009)	0.0040*** (0.0009)
log(U in 21-50th submarket)				-0.0045*** (0.0012)	-0.0044*** (0.0012)	-0.0044*** (0.0011)
N applications in first month						-0.0001*** (2.64e-5)
Personal characteristics	No	No	Yes	Yes	Yes	Yes
Elapsed spell duration	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker residence	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occupation (3-dig)	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Commuting zone	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Part time	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Quarter	No	No	No	No	Yes	No
Observations	3,064,460	3,064,460	3,064,460	3,064,460	3,064,460	3,033,946
R2	0.01851	0.02777	0.03872	0.03874	0.03997	0.04788
Baseline probability	0.1037	0.1037	0.1037	0.1037	0.1037	0.1037
Number of unemp. spells	428,309	428,309	428,309	428,309	428,309	422,744

Estimates are based on OLS regressions. The dependent variable is the binary outcome of exiting unemployment within the next month. V and U in the Xth submarket represent the 3-month rolling average of the stock of vacancies and consideration-weighted unemployed individuals, in the jobseeker's Xth submarket ranked by the leave-one out prediction from the consideration model based on the jobseeker's characteristics. The sample contains all registered jobseekers initiating their unemployment spell between January 2019 and June 2021. It includes jobseekers with clicks and without on job-room.ch, except for the 60% of clickers used for the estimation of consideration probabilities. Data on unemployment spells, background characteristics, and job findings are obtained from administrative records, the vacancy information from X28. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the unemployment spell level.

and the model includes several detailed fixed-effects such as the location-occupation indicators. In my baseline estimates, I, therefore, employ a simple and fast linear probability model to estimate the hazard using a high-dimensional fixed effects regression based on OLS. I show robustness of the results using a complementary log-log specification of the hazard, $log(-log(1-P(Y=1|x))) = x'\beta$.

5.2.1 Results from the baseline estimation

Table 5 shows the results of the baseline specification regressing the unemployment exit probability on the stock of vacancies, differentiated by predicted consideration of those vacancies.

Column (1) introduces the correlation between job vacancies in the most considered submarkets and the probability of jobseekers exiting unemployment, with controls limited to unemployment duration to shut down any duration dependence effects and time effects to account for overall economic activity. The analysis reveals that a statistically significant and positive correlation coefficient between the count of vacancies in the 1-10th most considered submarkets and the the likelihood of exiting unemployment the next month. In contrast, the effects of vacancies in the 11-20th submarkets are insignificant, and vacancies in the 21-50th submarkets have a negative correlation with unemployment exit probabilities.

Column (2) adjusts the analysis to account for occupation, location, and part-time preferences, alongside their interactions. This approach ensures comparisons are made among jobseekers located in the same labor market. After incorporating these controls, the analysis finds that vacancies in the 1-10th most considered submarkets continue to correlate with an increased probability of exiting unemployment, albeit with a reduced effect compared to Column (1). Vacancies in the 11-20th and 21-50th submarkets show negative correlations with the likelihood of exiting unemployment.

Column (3) incorporates controls for personal characteristics, including gender, parenthood, age, nationality (non-Swiss), education, and experience in the last occupation. This addition addresses a potential omitted variable bias. Personal characteristics not only influence the probability of job finding but also shape the scope of job consideration by altering the weight given to factors like commuting distance, occupation match, and match in hours. By explicitly modeling and predicting consideration probabilities on a leave-out sample, the research design controls for the full set of factors affecting the consideration scope. The analysis reveals a differential impact of job openings across considered submarkets. There is a significant positive effect of vacancies in the 1-10th most considered submarkets on the likelihood of exiting unemployment, with a coefficient of 0.0023. As expected, the effect for the 11-20th ranked submarkets is lower but still positive and significant, with a coefficient of 0.0006, indicating that while these jobs are less influential, they still positively impact employment outcomes. Beyond the 20th rank, the effect of job openings becomes insignificant and very close to zero, suggesting a threshold in the matching process where additional openings cease to predict unemployment exit probabilities.

The interpretation of the effect magnitudes is not straightforward as the independent variable is the stock of vacancies. Arguably the stock is the right measure to count the number of active job opportunities in a month. However, taking the stock instead of the flow leads to a vacancy being in the dataset for a jobseeker in several months, while the hazard is just measured once, leading to an understatement of the estimated effect[22]. To address the issue, I run a counterfactual exercise. The exercise shows that, for the average jobseeker, the job openings in the ten most considered submarkets contribute around 7% to the probability of leaving unemployment within six months (Baseline probability = 0.57)[23]. The contribution to the six-month exit hazard of job openings in

[22]This issue is further amplified by the fact that I take the average stock of vacancies over the past three months in order to not having to assume an exact lag between an opening and job finding.

[23]For every jobseeker, I predict the hazard rate for their first 6 months of the spell (even if they actually left unemployment earlier than this). I run the prediction once with the average number of job openings in the 10 most considered submarkets and once with just one job opening in the submarkets (one being the lowest count for which the logarithm is defined) . I then average the hazard rates over all jobseekers and take the difference in survival after 6 months between the two predictions. Averaging ensures that the prediction is obtained at mean effect of all

the 11th-20th submarkets is 2% and the openings in subsequent submarkets do not alter the exit hazard. The other factors affecting the hazard rate are personal characteristics, occupational and location factors as well as cyclicality in job finding probabilities. To compare, having university education contributes 1.8%, and having a child reduces the six-month hazard by 16%.

The results highlight the complexity of the job market, suggesting that not all jobs within a conventional cell, such as occupation by commuting zone, are equally considered and all jobs outside of the cell are irrelevant, as frequently assumed in existing research. Instead, it shows that job consideration is a more nuanced process, and the importance of job openings is lower in less preferred submarkets. The precision with which the model delineates the impact of job openings, is particularly remarkable considering that the model combines clicks, job openings and spell records from three completely independent data sources.

Figure 5 presents the results from column (3), graphically showing the decay in the effect of job openings moving from the 10 most considered submarkets to less considered submarkets. At the median over jobseekers and months, the 10 most considered submarkets contain 139 vacancies, the next 10 submarkets contain 112 vacancies, and the next 30 sub-markets contain 473 vacancies.

The predicted consideration probabilities are time-constant, shutting down any potential inter-linkages between increases in the job postings in a submarket and increases in consideration of the submarket. However,there might still be a concern that jobseekers concentrate their search efforts toward submarkets characterized by constantly high job opening rates. Such behavior could elevate competition within these submarkets, mitigating the positive impact of job openings on individual job-finding probabilities. In Column (4), I account for the competition in the submarkets by adding the number of jobseekers, weighted by their probability to consider the respective submarkets (U) to the analysis. Controlling for the number of unemployed jobseekers across submarkets holds competition constant, estimating the effect of job openings compared to jobseekers in submarkets with a similar number of other jobseekers. The column reveals slightly adjusted coefficients for the impact of job openings in the most considered submarkets, maintaining a close resemblance to the findings in Column (3). The coefficient on vacancies in the 21st to 50th submarket increases compared to Column (2), but is still insignificant. Regarding the effect of the number of jobseekers, the coefficient on U in the 1-10th most considered submarkets indicates a decrease in job finding chances with an increase in competition, as expected. The coefficient is -0.0046, representing a 4.6% decrease in job finding probabilities associated with a 1 log-point increase in competition. For the 11-20th submarkets, the coefficient for U is 0.0042, suggesting an increase in job finding probabilities

occupation, location and calendar month fixed effects.

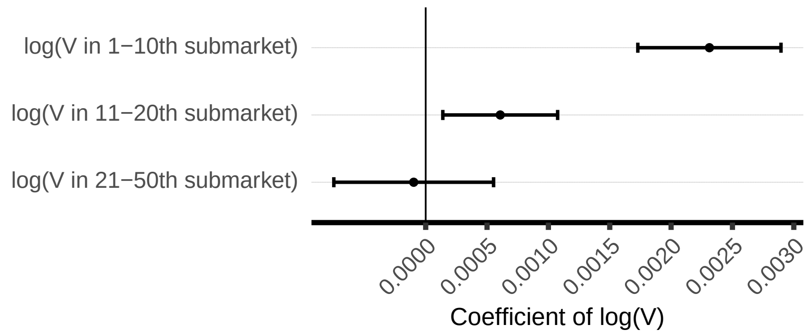
by approximately 0.42% relative to the baseline of 10.1%. This large positive coefficient is a puzzling finding. It is likely to be a feature of the fact that the consideration-probability weighting used in the computation of U smoothes out a lot of variation over submarkets and that the stocks of jobseekers do not vary as much over time as the stock of jobs. In a specification without location and occupation fixed effects, the effects are negative for all U variables. For submarkets beyond the 20th, the significant coefficient of -0.0045 corresponds to a decrease in job finding chances by approximately 0.45% against the baseline.

Column (5) addresses potential biases from sector-specific trends affecting job openings and job finding chances by introducing occupation-quarter dummies. This control for occupation-specific time trends slightly reduces the coefficients for job openings in the first two bins, indicating only minimal impact of these broad trends on the relationship between job openings and unemployment exits. The findings affirm the robustness of the analysis, demonstrating that the observed effects of job openings on job finding probabilities are consistent, even when accounting for sectoral influences.

A further concern in the estimation could be that the consideration breadth is related to the search intensity of a jobseeker. In the administrative record, there is information mirroring the search intensity: the number of applications sent per month. It is available for 403,169 of the 428,309 spells in the sample. Sending out applications is a requirement for receiving job benefits. A problem with including this measure of search intensity into the specification is that jobseekers who will start a new job within a month do not have to send applications, hence the current number of applications is a bad control. I use the number of applications in the first month of the spell. As Column (6) shows, including the search intensity into the estimation does not alter the results. The coefficient on search intensity is negative and significant, suggesting that jobseekers with worse employment prospects anticipate this disadvantage and send more applications, or are urged to do so by the caseworker.

In further checks for the robustness of the results, I first address the issue where 4,841 cases have a 3-month rolling average of vacancies in a submarket bin equal to zero; I implement a simple adjustment by adding 1 to the number of vacancies before taking the logarithm. The effect of this adjustment is minimal, resulting in a slight increase in the coefficients for job openings. Secondly, I switch from a linear model to a complementary log-log model. In that model, the impact of job openings in the 1-10th most considered submarkets remains consistent with previous findings, with almost identical marginal effects. The effect in the 11-20th ranked submarkets appears slightly lower and not statistically significant. Results are shown in Appendix Table 6, Columns (2) and (3), respectively.

Figure 5: Explaining job finding with job openings in most considered submarkets



This graph presents the coefficients on the number of vacancies on the unemployment exit probability, as captured in Column (3) of my regression analysis. The effect of the number of vacancies is allowed to vary across the predicted degree of consideration, effects for vacancies in 50 submarkets with the highest predicted consideration are estimated. The estimates control for personal characteristics, elapsed spell duration, calendar month, and include interaction terms for Part time x last occupation (2-dig) and a detailed set of fixed effects for last occupation and residence location and their interaction. The sample encompasses all registered jobseekers initiating their unemployment spell between January 2019 and June 2021. It includes jobseekers with and without clicks on job-room.ch, except for the 60% of clickers used for the estimation of consideration probabilities. Submarket consideration ranks are derived from out-of-sample predictions of our job consideration model. Error bars signify 95% confidence intervals. Data for spell dates, background characteristics, and job findings come from administrative records, with vacancy information from X28, and consideration ranks informed by the job consideration model.

Manning & Petrongolo (2017) emphasize the role of ripple effects diluting the impact of job creation in one segment of the economy across a series of overlapping markets. My results in Column (3) include these ripple effects, as I measure the effect of job openings on *any* job found by a jobseeker. The results in Column (4) control for the number of unemployed jobseekers. The reduced number of jobseekers is the channel through which the ripple effects work in Manning & Petrongolo (2017), hence this specification should in principle shut down those channels. However, this interpretation comes with several limitations: there might be on-the-job search, having a differential effect from the search of the unemployed measured here and if the direct effects manifest much faster than the ripple effects, both Columns (3) and (4) only measure the direct effect. Indeed the two specifications do not show any substantially different effects.

5.3 Mass-hiring events

To further address potential endogeneity in job openings relative to jobseekers' search scopes, this section introduces a novel measure based on unusually large spikes in hiring by single firms. When firms decide on the occupation and location of their new job openings, they might consider the number of available job seekers in those areas. This consideration could lead to concerns about the endogeneity of simple measures of job openings, as firms' choices may not be independent of jobseekers' availability. The mass-hiring events, are typically driven by product market developments rather than labor market condition and therefore potentially exogenous to local job seeker availability.

A hiring shock is defined as a firm posting 30 or more vacancies within a given month. 30 postings per month is around the 99th percentile of the distribution of number of vacancies created per firm and month. I further only take firm-months where the hiring shock is larger than the cumulative hiring of the firm over the past 18 months, to make sure those are unprecedented events. This restriction further has the advantage that it decouples the definition of shocks from the firm size: If a firm is large and hires frequently, the cumulative 18 months threshold will passed less often. I choose the duration of 1.5 years for the threshold to exclude spikes stemming from yearly hiring patterns, which are for example prevalent in the education sector. Between 2019 and mid-2021, I identify 53 mass-hiring events, creating jobs in 1322 submarkets.

The definition excludes vacancy postings recruitment agencies, including staffing and temporary firms, as they cannot be attributed to the hiring firm. Additionally, vacancy postings that appear online for less than 24 hours are omitted, as they are more likely to result from technical issues rather than represent real labor demand shocks.

The number of job openings in a submarket is defined as the number of vacancies created in a submarket as a part of a hiring shock. Thus, a hiring shock can affect several submarkets. I account for the potential lag between job opening and job finding by using the 3-month cumulative sum of the mass-hiring shocks per submarket.

5.3.1 Results using mass-hiring shocks

This specification introduces an analysis of mass hiring events as potentially exogenous shocks to job openings, focusing on unusually large spikes in hiring by single firms. The effect of a 10-vacancy increase in the most considered submarkets (1-10th) on unemployment exit probabilities is positive across all specifications, starting with a significant conditional correlation of 0.0016 in column (1). In Column (3), controlling for all personal characteristics, the location and the last occupation of a jobseeker, the effect is 0.0009, equivalent to a 0.87% increase in the job finding probability. For the 11-20th ranked submarkets, the effect is more nuanced, with the preferred specification in column (3) showing a coefficient of 0.0006, indicating a slight but statistically significant increase in unemployment exit probabilities, equivalent to a 0.57% increase against the baseline. This suggests that, while less pronounced, mass hiring events in these moderately preferred submarkets still

Table 5: Explaining job finding with job openings stemming from mass-hiring by firms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment
Hiring shock in 1-10th submarket	0.0016*** (0.0002)	0.0011*** (0.0003)	0.0009*** (0.0002)	0.0010*** (0.0003)	0.0005 (0.0003)	0.0008*** (0.0002)
Hiring shock in 11-20th submarket	0.0014*** (0.0003)	-0.0002 (0.0003)	0.0006* (0.0003)	0.0005* (0.0003)	0.0004 (0.0003)	0.0003 (0.0003)
Hiring shock in 21-50th submarket	0.0006*** (0.0001)	1.59e-6 (0.0001)	-4.76e-5 (0.0001)	5.78e-6 (0.0001)	3.68e-5 (0.0001)	8.92e-7 (0.0001)
log(U in 1-10th submarket)				-0.0037*** (0.0010)	-0.0043*** (0.0010)	-0.0033*** (0.0010)
log(U in 11-20th submarket)				0.0049*** (0.0009)	0.0048*** (0.0009)	0.0045*** (0.0009)
log(U in 21-50th submarket)				-0.0040*** (0.0012)	-0.0039*** (0.0012)	-0.0038*** (0.0011)
N applications in first month						-0.0001*** (2.64e-5)
Personal characteristics	No	No	Yes	Yes	Yes	Yes
Elapsed spell duration	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker residence	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occupation (3-dig)	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Commuting zone	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Part time	No	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Quarter	No	No	No	No	Yes	No
Observations	3,076,914	3,076,914	3,076,914	3,017,600	3,017,600	3,038,765
R2	0.01821	0.02794	0.03893	0.03888	0.04012	0.04782
Baseline probability	0.1039	0.1039	0.1039	0.1039	0.1039	0.1039
Number of unemp. spells	430,106	430,106	430,106	430,106	430,106	404,816

Estimates are based on OLS regressions. The dependent variable in all models is the binary outcome of exiting unemployment within the next month. The analysis introduces "Hiring shock" variables in the 1-10th, 11-20th, and 21-50th submarkets, representing significant increases in vacancies due to mass hiring events, defined as a company posting 30 or more vacancies in a given month and more than in the previous 1.5 years combined. The shocks are measured in 10-vacancy units. U in each submarket signifies the 3-month rolling average of the stock of consideration-weighted unemployed individuals. The sample includes all registered jobseekers initiating their unemployment spell between January 2019 and June 2021, covering both individuals with and without interactions on job-room.ch. For those with clicks, the analysis excludes the 60% sample used for estimating consideration probabilities. Data for spell dates, background characteristics, and job findings come from administrative records, with vacancy information from X28, and consideration ranks from the job consideration model using data from job-room.ch. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively, with standard errors clustered at the unemployment spell-level.

contribute to jobseekers' chances of finding employment. In the 21-50th submarkets, the initial modest positive correlation is statistically insignificant in all further specifications, indicating no impact of mass hiring events on unemployment exits for less considered submarkets.

Column (4) shows that, as in the baseline specification, controlling for the consideration weighted number of unemployed in the submarkets does not substantially alter the picture. Column (5) incorporates controls for occupation-specific time trends. With this adjustment, the effects of hiring shocks in the most considered submarkets (1-10th) show a coefficient of 0.0005, which is smaller and not statistically significant compared to the findings in column (3). The decay in coefficients along the consideration probability is, albeit insignificant, still visible. Column (6) controls for the search intensity measured by the number of applications recorded in the unemployment register in the first month of the spell. Similar to Column (5), this specification confirms that the mass-hiring estimates are noisier and less robust to additional controls than the baseline. The coefficient on job openings in the top ten submarkets is similar to Column (3), the coefficient on the job openings in the 11-20th submarket is not significantly different from zero. The null effect of openings further down in the predicted consideration is not changed.

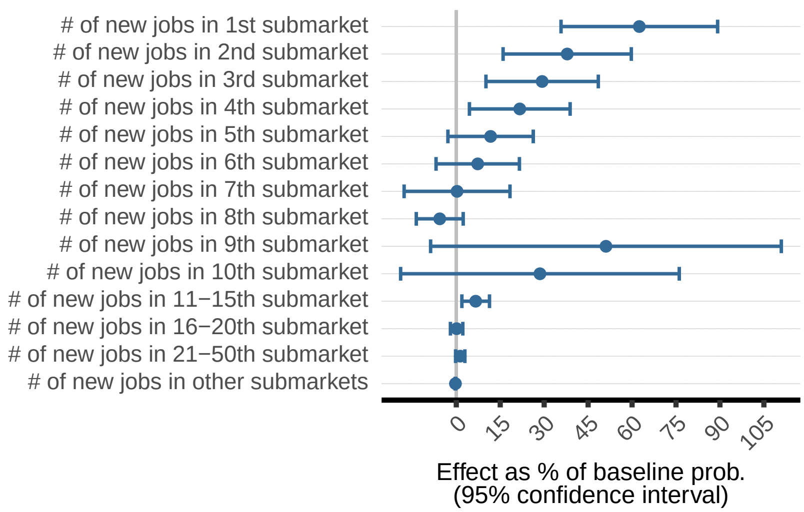
The magnitude of the estimates aligns very closely with the estimates from the baseline specification: if one converts the baseline effects of the log number of active vacancies to a average marginal effects, one finds that 1 additional vacancies in the ten most preferred submarkets increase the exit hazard in the next month by 0.084%. In my preferred mass-hiring specification in column (3), the effect of one created vacancy is 0.087%. The effect of job openings in the 11-20th submarkets is 0.057% in the mass-hiring specification compared to 0.023% in the baseline. Appendix Table 7 also reports marginal effects from a cloglog model using the mass-hiring shocks. The marginal effect of job openings in the first 10 submarkets is very similar to the effect from the linear model. The effect of openings in the 11th-20th submarket is slightly lower and not significant at the 10% level. However, it's not significantly different from the baseline estimate either.

If one were to use the mass-hiring as an instrument for the number of vacancies used in the baseline specification, the results presented in Table 5 would be the reduced form and would be scaled up using the first-stage impact of hiring shocks on the stock of vacancies. Such an instrument would be based on the assumption that hiring shocks only affect job finding through the increase in job openings. I argue that this exclusion restriction is rather unrealistic since a mass-hiring shock at a firm might also affect other parameters of the matching function. For instance, if a firm is in need of a large increase in workforce, its recruiters might be less picky in filtering out applicants which would affect the probability of getting hired conditional on applying. Therefore, I believe that the coefficient on the "reduced form" shown here is the coefficient of interest and scaling up these coefficients by a "first stage" would lead to overstated effects.

5.4 Direct effects of shocks on job finding

This analysis leverages that the unemployment records contain the re-employment firm name. I examine the influence of mass-hiring events on jobseekers' employment probabilities at the firms conducting these hirings. I construct a dataset of all pairs of jobseekers and firm mass-hiring events that occur during or within in the six months before a jobseeker's unemployment spell. The outcome is whether the jobseeker finds a job at the hiring firm within twelve months of the hiring shock. The firm names from the administrative records are compared to the firm names of the hiring firms using fuzzy string matching. There is a substantial part of jobseekers who find a job but without firm information on the new job in the administrative data. I make a conservative imputation and assume that they did not find a job at the hiring company. Alternatively omitting

Figure 6: The effect of mass-hiring on job finding at a hiring firm



Effect of a mass-hiring event on finding a job at the hiring firm. The estimates are from an OLS regression of a binary variable indicating whether the individual found a job at the hiring firm within 12 months of the hiring shock. One observation is a jobseeker-shock pair. The explaining variables are the number of vacancies created in the mass-hiring shock. The number of vacancies is interacted with the submarket in which the vacancies are created. For every jobseeker, all the submarkets are ranked by the leave-out prediction of the probability that the individual considers the submarket given the individuals personal characteristics, location, last occupation and workload preference. The regression controls for the jobseekers personal characteristics, location, last occupation and part-time preference, the calendar month of the hiring-shock, as well as as for the number of months elapsed in the jobseeker's unemployment spell at the time of the shock. The effects are reported as a percentage of the baseline probability, 0.008%, of a jobseeker finding a job at the mass-hiring company. N = 8 404 025. Standard errors are clustered at the unemployment spell-level.

those observations does not alter the results. The final dataset contains 7'791'140 jobseeker-shock observations stemming from 428 309 unemployment spells. I estimate an OLS regression on the dataset of jobseeker-shock pairs, focusing on the interaction between vacancy numbers and jobseekers' most preferred submarket. The submarkets are ranked based on the leave-out prediction of the probability of consideration a submarket given the jobseekers personal characteristics, geographic location, past occupation, and workload preference. I control for the personal characteristics, the jobseeker's location and last occupation, the interaction between the two, the interaction between the jobseeker's part time preference and the occupation, the month elapsed since unemployment start at the time of the shock, and a calendar month fixed effect.

The results in Figure 6 and Appendix Table 9 illustrate a clear decay in the impact of new vacancies on employment probabilities across ranked submarkets. Specifically, the coefficient on new jobs in the first-ranked submarket is an increase in job finding probability at the hiring firm of 62% relative to the baseline probability. The effect diminishes as one moves to lower-ranked submarkets, the coefficient for the forth-ranked submarket represents at 22% increase in probability, significantly different from 0 at the 10%-level.

The submarkets analyzed in the study are notably small, containing only around 20 vacancies each (at the median). That the consideration model is able to identify at such a granular level where within the economy hiring shocks are likely to exert the highest effects on job seekers is remarkable.

This analysis of direct effects reveals that the impact of mass hiring events becomes insignificant for submarkets ranked beyond the fourth. In contrast, the mass-hiring specification still identifies a significant impact on employment probabilities within the 11-20th ranked submarkets, suggesting a broader influence of these events. However, in the direct effect estimation, when we move to more aggregate bins of markets, after the 10th submarket, the standard errors get smaller again and I find a significant effect. This suggests that the main source of discrepancies is the statistical power. A further difference may be attributed to spillover effects. A mass hiring event might not only benefit those job seekers who secure positions at the hiring firm but could also indirectly advantage other job seekers through a reduction in competition.

6 Narrow and broad consideration

An interesting question is whether the decay of the effect of job openings in less considered submarkets is uniform across all jobseekers or not. I investigate whether individuals who are likely to distribute their consideration across more occupations and locations also benefit from job openings in more submarkets. I measure the narrowness of consideration using the cumulative predicted probability of considering the 10 highest ranking markets. Analogous to the literature using discrete choice models in market research, one could call the cumulative probability of considering the 10 most preferred submarkets the 'market share' of those submarkets relative to the total consideration of a jobseeker.

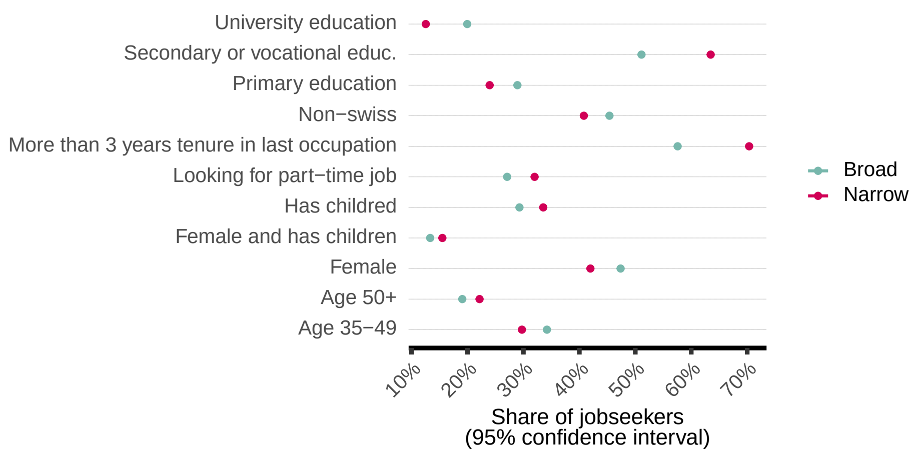
If this probability is high, it means that the first 10 markets have a high share in the total consideration relative to the other markets. For the median jobseeker, the share of consideration that goes to the first 10 submarkets is 8.0%, for a very 'broad' jobseeker the share is 5.1% (10th percentile) and for a very 'narrow' jobseeker, who puts a lot of weight on few submarkets, the share is 9.4% (90th percentile). I construct an indicator variable, categorizing a jobseeker as having narrow consideration if the share is higher than the median[24].

Figure 7 shows the characteristics of jobseekers who are predicted to consider jobs broadly according to the definition outlined and compares them to jobseekers with a narrow predicted consideration. There are sizeable difference in the educational backgrounds, workers with university education are likely to search broadly. At the same time, workers with secondary and vocational education, which is frequently occupation-specific, tend to focus more narrowly. Also jobseekers with high occupation-specific experience tend to consider jobs more narrowly. When looking at the family situation, being a parent of a minor is associated with a more narrow search and females tend to distribute their consideration over more submarkets, on average.

Figure 8 and Appendix Table 10 present results for the effect of job openings in different submarkets on job finding interacted with whether the jobseeker is narrow or broad in their consideration. Panel (a) uses the baseline specification, where job openings are measured using the rolling average of the stock of vacancies. Job openings in the 1-10th most considered submarkets have a notable positive effect on the probability of exiting unemployment for both broad and narrow jobseekers. Jobseekers with a broad consideration scope show a coefficient of 0.0014. For the narrow type, the effect is twice as large, 0.0028. This suggests that while all jobseekers benefit from more job openings in the most considered submarkets, those who focus more narrowly are also able to leverage those job openings more and find employment. For the 11-20th submarkets, the positive impact of job openings persists for jobseekers with broad consideration, albeit at a slightly lower rate of 0.0009. However, for those with narrow consideration, the coefficient is close

[24] In the remainder of the section I will use the words 'narrow' and 'broad' to refer to jobseekers who, given their personal characteristics, last occupation and location, are likely to distribute their consideration narrowly or braodly over submarkets, respectively.

Figure 7: Characteristics of jobseekers with narrow and broad consideration focus



The figure shows the distribution of jobseekers within our sample, distinguishing between those with 'narrow' and 'broad' consideration focuses. 'Narrow' jobseekers are defined as those with a cumulative predicted consideration probability for their top 10 submarkets at or above the median. The share of jobseekers represents the proportion of individuals in our sample exhibiting each characteristic, with the dotted lines indicating the 95% confidence interval based on the standard error of the mean for these proportions. Source: Administrative data, own calculations based on administrative data and clicks on job-room.ch.

to zero and insignificant, indicating that jobseekers who focus their search on fewer submarkets do not experience the same benefits from job openings in less preferred submarkets. Job openings in the 21-50th submarkets show no significant effect on the unemployment exit probability, regardless of the consideration scope, indicating that jobseekers are less responsive to hiring shocks in these less considered submarkets regardless of their search breadth.

To further illustrate the differential importance of job openings for the two types, as in Section 5.2.1, one can translate the results into contributions of the job openings in different submarkets to the 6-month job finding hazard[25]. For the broad type, the job openings in the ten most considered submarkets contribute 4.4% to the probability of finding a job within 6 months, and the openings in the 11-20th submarkets contribute 2.5%. For the narrow type, the contribution of the top 10 submarkets is much larger, at 9.7%, while the contribution of the 11-20th submarket is close to zero and insignificant.

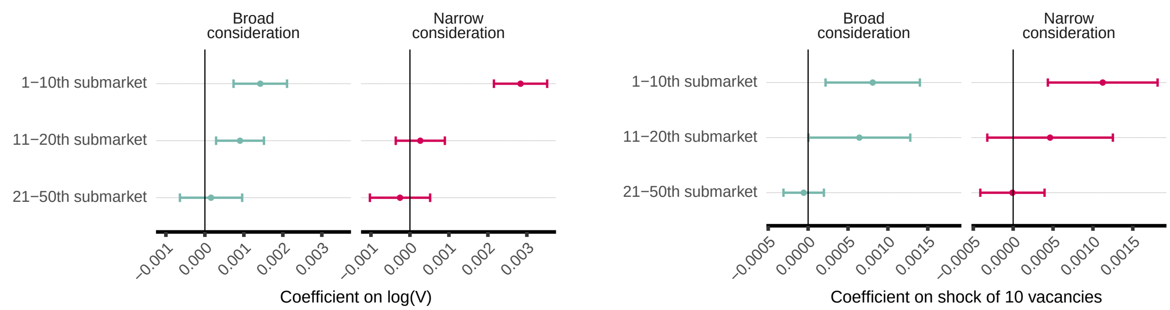
In Panel (b), the estimates based on mass-hiring shocks offer a parallel yet less precise reflection of the patterns observed in Panel (a). The effect of hiring shocks in the 10 most preferred submarkets is larger for jobseekers with a narrow consideration scope, although the difference is not statistically significant. The impact of job openings in the 11-20th submarkets shows a positive effect (significant

[25] To compute the counterfactual, I proceed as in footnote 23. I hold all the jobseeker characteristics and vacancy counts constant at averages and only change whether I apply the coefficients for the narrow or the broad type.

at the 10% level) for those with broad to medium consideration but is zero for jobseekers with a narrow focus. For the 21-50th submarkets, the effect of job openings is not significantly different from zero for both groups.

The estimates shown control for the personal characteristics as well as for the jobseekers' last occupation, residence location, part-time preference and their interactions. Additionally controlling for the number of consideration-weighted jobseekers (U) confirms the findings from the graphs, with only slight deviations in the magnitude of the effects (Appendix Table 10). Controlling for the search intensity and occupation-specific time trends does not change the results from the baseline specification, if anything the patterns are more pronounced. The results form the mass-hiring specification are noisy and more sensitive to the inclusion of additional controls.

Figure 8: Heterogeneity of the effect of job openings on job finding by the narrowness of consideration



(a) Estimates based on the stock of vacancies (Baseline specification)

(b) Estimates based on mass-hiring shocks

This graph presents heterogeneous effects of the number of vacancies on the unemployment exit probability, based on Appendix Table 10 Columns (1) and (5). It differentiates jobseekers by the breadth of their job search, categorized as "narrow" for those focusing on few submarkets and "Broad" distributing their consideration over many. "Narrow" is defined by a high ($\geq$ median) cumulative predicted consideration probability for the top 10 submarkets. Panel (a) reflects the baseline specification with job openings as a 3-month rolling average, while Panel (b) evaluates the impact of significant hiring spikes defined as a firm posting 30 or more vacancies in a given month and more than in the previous 1.5 years combined. The estimates control for personal characteristics, elapsed spell duration, calendar month, and include interaction terms for a set of fixed effects for last occupation, residence location, part-time preferences and their interaction. The sample contains all registered jobseekers starting their unemployment spell between January 2019 and June 2021, both those with clicks on job-room.ch and those without, except for the 60% of clickers used to estimate consideration probabilities. Submarket consideration ranks are derived from the job consideration model using data from job-room.ch. Data for spell dates, background characteristics, and job findings come from administrative records, vacancy information from X28. Error bars signify 95% confidence intervals.

The advantage that narrow jobseekers have in benefiting from jobs in their ten most considered submarkets is larger than the disadvantage they have compared to broad jobseekers in the 11th to 20th submarkets when it comes to leveraging job openings to find employment. Assuming job openings are uniformly distributed across submarkets, narrow jobseekers should, in theory, benefit more from such openings. This hypothesis is supported by a simulation that uses the actual distribution of job openings observed in the data. The simulation contrasts narrow and broad jobseekers multiplies the coefficients from the model with the actual number of job openings, holding all characteristics apart form the search scope constant. The results of this back-of-the-envelope calculation suggest that the difference is very small compared to other fluctuations in the job finding rate over time. Narrow jobseekers consistently exhibit a higher probability—around 0.3 percentage points—of exiting unemployment within three months compared to the average exit probability of 32%, as depicted in Appendix Figure 12. This small difference suggests that when accounting for the actual distribution of vacancies, the two search strategies on average cancel out in their effects on the job finding rate.

7 Conclusion

My study shows that combining online search data with administrative data can reveal 'real world' facts. I project consideration scopes estimated from clicks on job postings onto a panel of jobseekers. I find that these out-of- sample predictions are actually able to identify the segments of the economy where job openings have the most impact on job finding.

I find a steady decline of the effect of job openings with consideration: Job openings in submarkets which are predicted to be the most considered by a jobseeker have the highest effects on the jobseeker's unemployment exit probability. This job finding elasticity steadily declines when moving to submarkets with a lower consideration probability and there is no effect from the 21st most considered submarket onwards. I distinguish between two types of jobseekers: broad and narrow jobseekers. Broad jobseekers are those who, given their characteristics and the prediction from the job consideration model are likely to spread their consideration across a wide range of submarkets. And narrow jobseekers are those who, given their characteristics, are predicted to focus their search on few submarkets.

In my baseline specification, I show that a broader consideration is not necessarily associated with better job finding. Instead, jobseekers with a more focused consideration set can better leverage the job openings within that narrower scope, compared to their counterparts who distribute their consideration more broadly. This suggests that jobseekers adapt their focus to reflect their job-finding probabilities in different segments of the economy. One implication for this is that job search advice with the aim to broaden the search scope is not necessarily beneficial: if we advise narrow jobseekers to search broadly this may divert their attention to segments of the market with a lower job finding probability for them. Broad jobseekers seem to be able to benefit from job openings in a wide range of the economy. For those jobseekers, advice can potentially help to find segments to concentrate their search on. I outline a range of observable characteristics that go along with broad consideration and being able to broadly leverage job openings, for instance university education, non-Swiss nationality and being a woman without childcare obligations.

A similar argument can be applied to place-based policies, or also industry-based policies, that try to promote job growth in a particular localization of the economy. Manning & Petrongolo (2017) make the argument that geographical local labour markets are overlapping thereby diluting the impact of place-based policies through ripple effects. My findings suggest that this average effect is likely to predominantly apply to the broad type of jobseekers, as their labor markets are even more overlapping with other jobseekers. The narrow type of jobseekers is able to highly leverage 'local' job openings with respect to occupation and location to find a job themselves. This implies that the narrow type of jobseekers, such as workers with occupation-specific education or experience but also parents, especially mothers, might be able to substantially benefit from government stimuli in their location or industry.

My study underscores the potential for future research to explore the differential impacts of labor market policies, such as place-based or industry-based initiatives, on broad versus narrow jobseekers. Given the distinct ways in which these two groups leverage job openings within their respective consideration sets, understanding the differential effects of such policies could lead to more targeted and effective interventions. A direct extension of this study could use wage data of the jobs upon re-employment and add an analysis of the intensive margin of job quality to this analysis of the extensive margin of job finding.

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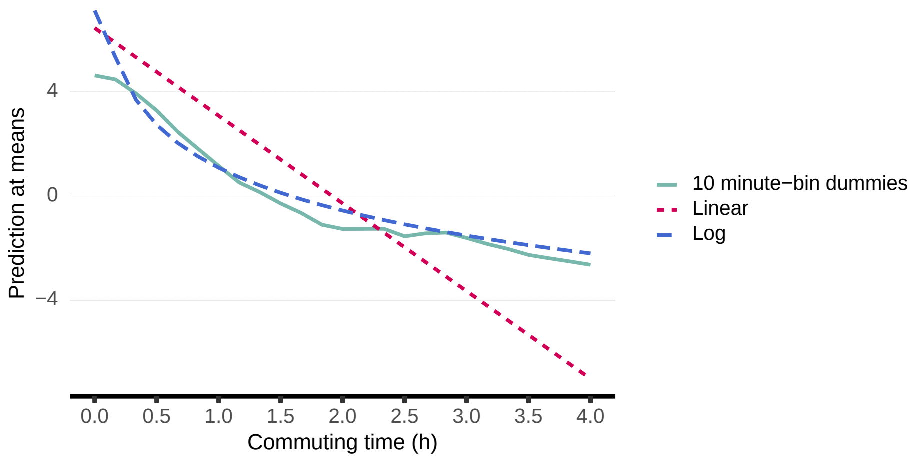
Figure 9: Functional form of the effect of the commuting distance on job consideration



Predictions at means from different functional forms of the commuting time. Estimates from fixed-effects Poisson regressions on expanded data containing an observation for every jobseeker–month-submarket tripled where the dependent variable is the number of clicks by the person on the submarket in the given month. The regession further includes the occupation match at the 2- and 3-digit level, the hours worked match and the inclusive value of the submarket. Only jobseeker-months with at least one click are included. For every jobseeker-month only submarkets with at least one vacancy posting that was online at the day the jobseeker was active on the platform are included.

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Appendix

Table 6: Robustness: Explaining job finding with job openings in most considered submarkets

	(1)	(2)	(3)
Dependent Var.:	Exit unemployment	Exit unemployment	Exit unemployment
log(V in 1-10th submarket)	0.0025*** (0.0003)	0.0027*** (0.0003)	0.0025*** (0.0004)
log(V in 11-20th submarket)	0.0006** (0.0002)	0.0006** (0.0003)	0.0002 (0.0003)
log(V in 21-50th submarket)	0.0004 (0.0004)	0.0004 (0.0004)	-5.67e-6 (0.0004)
log(U) in the 3 bins	Yes	Yes	Yes
Personal characteristics	Yes	Yes	Yes
Elapsed spell duration	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes
Jobseeker residence	Yes	Yes	Yes
Jobseeker occupation (3-dig)	Yes	Yes	Yes
Jobseeker occ (2-dig) x Commuting zone	Yes	Yes	Yes
Jobseeker occ (2-dig) x Part time	Yes	Yes	Yes
Model	OLS	OLS, log(V+1)	cloglog (marg. effect)
Observations	3,064,460	3,069,301	3,064,400
Pseudo R2	0.08554	0.08549	0.06018
Baseline probability	0.1037	0.1037	0.1037
Number of unemp. spells	428,309	430,106	430,106

Estimates are based on OLS regressions for Columns (1) and (2) and a complementary log-log regression for Column (3), reporting average marginal effects. The dependent variable in all models is the binary outcome of exiting unemployment within the next month. V and U in Xth submarket represent the 3-month rolling average of the stock of vacancies and consideration-weighted unemployed individuals, in the jobseeker's Xth ranked submarket preference. The sample encompasses all registered jobseekers initiating their unemployment spell between January 2019 and June 2021 and includes both those with clicks and those without on job-room.ch, except for the 60% of clickers used for the estimation of consideration probabilities. Data on unemployment spells, background characteristics, and job findings are obtained from administrative records, with vacancy information from X28, and submarket consideration ranks derived from out-of-sample predictions of a job consideration model. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the unemployment spell-level.

Table 7: Robustness: Explaining job finding with job openings stemming from mass-hiring by firms

	(1)	(2)
Dependent Var.:	Exit unemployment	Exit unemployment
Hiring shock in 1-10th submarket	0.0009*** (0.0002)	0.0009*** (0.0002)
Hiring shock in 11-20th submarket	0.0006** (0.0003)	0.0003 (0.0002)
Hiring shock in 21-50th submarket	-4.78e-5 (0.0001)	-6.57e-5 (0.0001)
log(U) in the 3 bins	No	Yes
Personal characteristics	Yes	Yes
Elapsed spell duration	Yes	Yes
Calendar month	Yes	Yes
Jobseeker residence	Yes	Yes
Jobseeker occupation (3-dig)	Yes	Yes
Jobseeker occ (2-dig) x Commuting zone	Yes	Yes
Jobseeker occ (2-dig) x Part time	Yes	Yes
____________________________________	__________________	__________________
Model	OLS	cloglog (marg. effect)
Observations	3,076,914	3,069,246
Pseudo R2	0.08561	0.06010
Baseline probability	0.1039	0.1039
Number of unemp. spells	430,106	428,458

Estimates are based on OLS regressions for Columns (1) and (2) and a Logit regression for Column (3), reporting average marginal effects. The dependent variable in all models is the binary outcome of exiting unemployment within the next month. The analysis introduces "Hiring shock" variables in the 1-10th, 11-20th, and 21-50th submarkets, representing significant increases in vacancies due to mass hiring events, defined as a company posting 30 or more vacancies in a given month and more than in the previous 1.5 years combined. These shocks are considered in 10-vacancy units. U in each submarket signifies the 3-month rolling average of the stock of consideration-probability-weighted unemployed individuals. The sample includes all registered jobseekers initiating their unemployment spell between January 2019 and June 2021, covering both individuals with and without interactions on job-room.ch. For those with clicks, the analysis excludes the 60% sample used for estimating consideration probabilities. Data for spell dates, background characteristics, and job findings come from administrative records, with vacancy information from X28, and consideration ranks informed by our job consideration model. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively, with standard errors clustered at the unemployment spell-level.

Table 8: The effect of mass-hiring on job finding at a hiring firm

	OLS coefficient	Percent of baseline prob.
Dependent Var.:	Find job at firm	Find job at firm
# of new jobs in 1st submarket	4.69e-5*** (1.02e-5)	62.48*** (13.64)
# of new jobs in 2nd submarket	2.84e-5*** (8.38e-6)	37.86*** (11.17)
# of new jobs in 3rd submarket	2.2e-5*** (7.35e-6)	29.30*** (9.784)
# of new jobs in 4th submarket	1.63e-5** (6.58e-6)	21.67** (8.769)
# of new jobs in 5th submarket	8.79e-6 (5.58e-6)	11.71 (7.431)
# of new jobs in 6th submarket	5.5e-6 (5.45e-6)	7.321 (7.260)
# of new jobs in 7th submarket	1.96e-7 (6.92e-6)	0.2608 (9.218)
# of new jobs in 8th submarket	-4.24e-6 (3.07e-6)	-5.647 (4.086)
# of new jobs in 9th submarket	3.84e-5* (2.29e-5)	51.09* (30.54)
# of new jobs in 10th submarket	2.14e-5 (1.82e-5)	28.56 (24.26)
# of new jobs in 11-15th submarket	4.97e-6*** (1.81e-6)	6.624*** (2.406)
# of new jobs in 16-20th submarket	8.79e-8 (8.09e-7)	0.1171 (1.078)
# of new jobs in 21-50th submarket	1.01e-6* (6.08e-7)	1.347* (0.8092)
# of new jobs in other submarkets	-2.17e-7*** (4.13e-8)	-0.2886*** (0.0550)
Female	-2.42e-7 (1.25e-5)	-0.3224 (16.62)
Age 35-49	8.61e-6 (1.02e-5)	11.47 (13.56)
Age 50+	-2e-5* (1.05e-5)	-26.60* (14.04)
Has children	-1.1e-5 (1.02e-5)	-14.61 (13.62)
Female x has children	-3.68e-6 (1.62e-5)	-4.896 (21.58)
Non-Swiss	-6.66e-6 (8.29e-6)	-8.874 (11.04)
Primary or lower sec. education	-1.03e-5 (9.58e-6)	-13.69 (12.76)
University education	2.82e-6 (1.48e-5)	3.749 (19.75)
3+ years tenure in last occupation	-6.01e-6 (9.55e-6)	-8.008 (12.71)
Calendar month	Yes	Yes
Elapsed spell duration	Yes	Yes
Jobseeker residence	Yes	Yes
Jobseeker occupation (3-dig)	Yes	Yes
Jobseeker occ (2-dig) x Commuting zone	Yes	Yes
Jobseeker occ (2-dig) x Part time	Yes	Yes
---	-------------------------	-----------------------
Observations	7,791,140	7,791,140
$R2$	0.00028	0.00028
Within R2	7.87e-5	7.87e-5

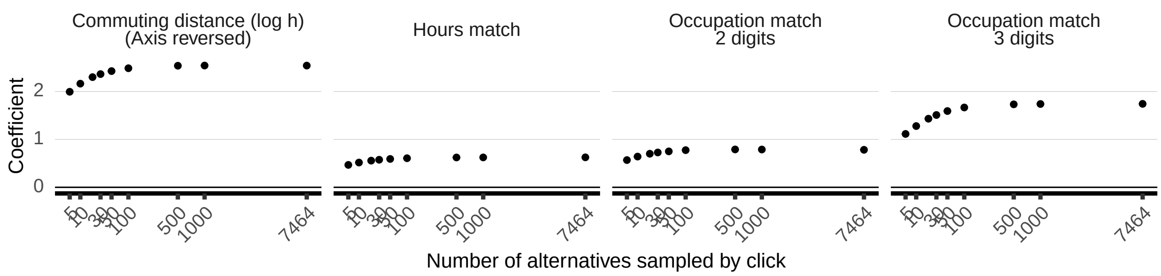
Table 9: Effect of a mass-hiring event on finding a job at the hiring firm. The estimates are form an OLS regression of a binary variable indicating whether the individual found a job at the hiring firm within 12 months of the hiring shock. One observation is a jobseeker-shock pair. The explaining variables are the number of vacancies created in the mass-hiring shock. The number of vacancies is interacted with the submarket in which the vacancies are created. For every jobseeker, all the submarkets are ranked by the leave-out prediction of the probability that the individual considers the submarket given the individuals personal characteristics, location, last occupation and workload preference. The regression controls for the jobseekers personal characteristics, location, last occupation and part-time preference, the calendar month of the hiring-shock, as well as as for the number of months elapsed in the jobseeker's unemployment spell at the time of the shock. The baseline probability of a jobseeker finding a job at a mass-hiring company is 0.008%.

Table 10: Heterogeneity of the effect of job openings on job finding by the narrowness of consideration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.:	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment
log(V in 1-10th submarket)	0.0014*** (0.0004)	0.0015*** (0.0004)	0.0015*** (0.0003)	0.0011*** (0.0004)				
log(V in 11-20th submarket)	0.0009*** (0.0003)	0.0009*** (0.0003)	0.0008*** (0.0003)	0.0008** (0.0003)				
log(V in 21-50th submarket)	0.0002 (0.0004)	0.0008* (0.0004)	0.0008* (0.0004)	0.0009** (0.0004)				
Narrow x log(V in 1-10th submarket)	0.0014*** (0.0004)	0.0015*** (0.0004)	0.0014*** (0.0004)	0.0016*** (0.0004)				
Narrow x log(V in 11-20th submarket)	-0.0006 (0.0005)	-0.0007 (0.0005)	-0.0007* (0.0004)	-0.0006 (0.0005)				
Narrow x log(V in 21-50th submarket)	-0.0004 (0.0005)	-0.0005 (0.0005)	-0.0004 (0.0005)	-0.0006 (0.0005)				
Hiring shock in 1-10th submarket					0.0008** (0.0003)	0.0008** (0.0003)	0.0007** (0.0003)	0.0004 (0.0004)
Hiring shock in 11-20th submarket					0.0006* (0.0004)	0.0006 (0.0004)	0.0004 (0.0004)	0.0005 (0.0004)
Hiring shock in 21-50th submarket					-5.54e-5 (0.0001)	-2.37e-5 (0.0001)	-3.11e-6 (0.0001)	3.5e-6 (0.0001)
Narrow x Hiring shock in 1-10th submarket					0.0003 (0.0005)	0.0003 (0.0005)	0.0001 (0.0005)	0.0003 (0.0005)
Narrow x Hiring shock in 11-20th submarket					-0.0002 (0.0006)	-0.0002 (0.0006)	-0.0001 (0.0006)	-0.0002 (0.0006)
Narrow x Hiring shock in 21-50th submarket					4.61e-5 (0.0003)	3.52e-5 (0.0003)	5.83e-5 (0.0002)	3.53e-5 (0.0003)
Narrow	-0.0039* (0.0020)	-0.0037* (0.0020)	-0.0033* (0.0020)	-0.0042** (0.0020)	-0.0030*** (0.0005)	-0.0031*** (0.0005)	-0.0028*** (0.0005)	-0.0031*** (0.0005)
N applications in first month			-0.0001*** (2.64e-5)				-0.0001*** (2.64e-5)	
log(U) for the 3 bins	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Personal characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Elapsed spell duration	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker residence	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker occupation (3-dig)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Commuting zone	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Part time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobseeker occ (2-dig) x Quarter	No	No	No	Yes	No	No	No	Yes
Observations	3,064,460	3,064,460	3,033,946	3,064,460	3,076,914	3,069,301	3,038,765	3,069,301
R2	0.03874	0.03875	0.04789	0.03999	0.03894	0.03870	0.04783	0.03993
Baseline probability	0.1037	0.1037	0.1037	0.1037	0.1039	0.1037	0.0974	0.1037
Number of unemp. spells	428,309	428,309	428,309	428,309	430,106	428,463	403,303	428,463

Estimates are based on OLS regressions. The dependent variable in all models is the binary outcome of exiting unemployment within the next month. The effect of the number of vacancies per predicted degree of consideration is interacted with the breadth of their job search, categorized as "narrow" for those focusing on few submarkets and "medium to broad" distributing their consideration over many. "Narrow" is defined by a high ($\geq$ median) cumulative predicted probability for the top 10 submarkets Columns (1) - (4) reflects the baseline scenario with job openings as a 3-month rolling average, while (5)-(8) evaluate the impact of significant hiring spikes defined as a firm posting 30 or more vacancies in a given month and more than in the previous 1.5 years combined. U in each submarket signifies the 3-month rolling average of the stock of consideration-weighted unemployed individuals. The sample includes all registered jobseekers initiating their unemployment spell between January 2019 and June 2021, covering both individuals with and without interactions on job-room.ch. For those with clicks, the analysis excludes the 60% sample used for estimating consideration probabilities. Submarket consideration ranks are derived from out-of-sample predictions of the job consideration model. Data for spell dates, background characteristics, and job findings come from administrative records, the vacancy information from X28. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively, with standard errors clustered at the unemployment spell-level.

Figure 10: Convergence of parameter estimates with random alternative sampling



Coefficients from the top nest model, as shown using the full sample in Table 2, Column (2). Estimates from fixed-effects Poisson regression on expanded data. For each click, X alternatives are randomly drawn from the distribution of all the other nests, the sampling probability is proportional to the number of clicks in the nest. The model is estimated on an expanded jobseeker-month panel containing an observation for every jobseeker–month-submarket triplet and the dependent variable is the number of clicks by the person on the submarket in the given month. The analysis uses data from job-room.ch, covering clicks between July 2020 and May 2021. The sample includes all registered jobseekers who began their unemployment spell within the sample period and recorded at least five clicks on the platform. Standard errors are clustered by jobseeker spell. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Figure 11: Simulated unemployment exit probability, broad vs narrow consideration

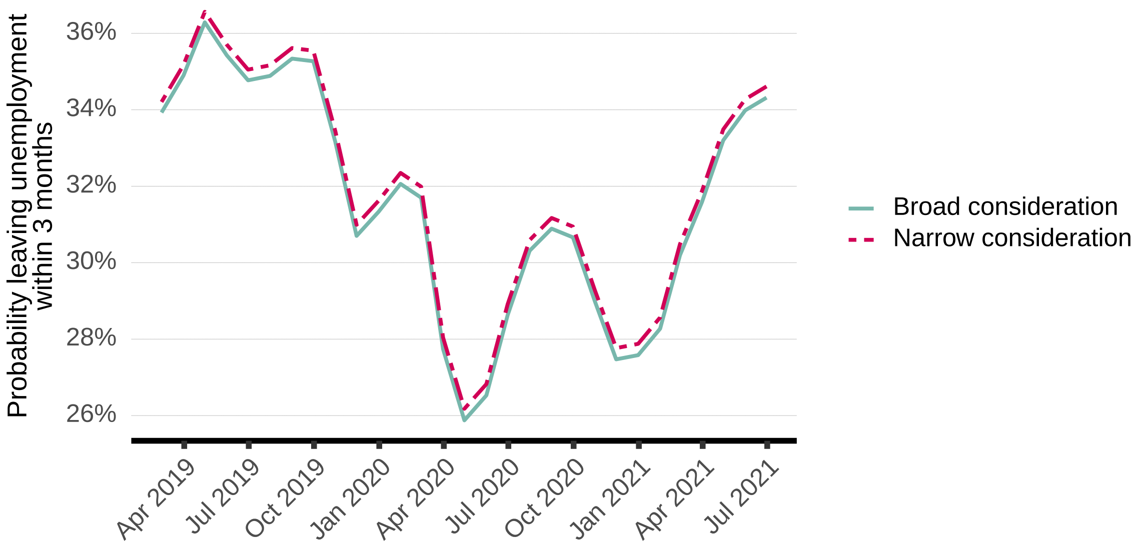


Figure 12: The simulation depicted in Figure 9 contrasts the unemployment exit probabilities between jobseekers with broad versus narrow consideration scopes, using the real distribution of vacancies. It differentiates jobseekers by the breadth of their job search, categorized as "narrow" for those focusing on few submarkets and "Broad" distributing their consideration over many. "Narrow" is defined by a high ($\geq$ median) cumulative predicted probability for the top 10 submarkets. The simulation employs coefficients from the baseline model to predict exit probabilities within three months, averaging personal characteristics across occupational and location cells. This process is repeated for each month, treating each cell's broad and narrow jobseekers as if starting their spell in the first month, with actual vacancy distributions informing the predictions. The effects of job openings in the 21-50th submarket is set to be exactly 0 instead of the noisily estiamted zero from the model. Results are then averaged over the cells for each group. The estimated shift in the hazard probability intercept for narrow jobseekers, which is 0.39 percentage points (3.9%) lower and significantly different from zero at the 10% level, is not factored into the simulation's predictions. The analysis utilizes data from all registered jobseekers who began their unemployment between January 2019 and June 2021, inclusive of those who did and did not interact with job-room.ch, excluding the 60% of clickers from whom consideration probabilities were estimated. Vacancy distributions are based on monthly data across submarkets from X28. The simulation uses the coefficients form the specification in Table 10 Column (1).

CHAPTER 2

Job Search and Employer Market Power

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Abstract

This paper provides a framework for thinking about how the job search of workers affects the market power of employers. We present a way of thinking about this which encapsulates popular existing models in which employer market power is based on either frictions in labor markets or imperfect substitutability among jobs. We show how this model can be used to compute measures of the extent of employer market power and relates them to popularly used measures of concentration ratios. We use data on the search behaviour of Swiss unemployed to investigate the number of employers being considered by job-seekers using 'clicks' on vacancies to define consideration sets.

1 Introduction

Actual or threatened worker mobility plays an important role in limiting the ability of employers to exploit their workers. But there is little focus in the job search literature on how it affects the competitiveness of labor markets though there is a very large literature on how the job search of the unemployed affects the duration of unemployment and the quality of the post-unemployment job. The approach taken in the paper is to analyze how the job search decisions of individual workers affects their consideration sets and how this affects the elasticity of the labor supply curve facing firms, a natural measure of employer market power.

Existing models tend to make assumptions about the consideration sets of workers. In the search model of Burdett and Mortensen (1998) (what Manning, 2020, calls modern monopsony) jobs arrive only occasionally and one at a time so that a worker has at most two employment

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possibilities at any time (their current job and the new possibility). Jobs are assumed to be perfect substitutes in the eyes of workers. In contrast, the model based on idiosyncracies e.g. Card et al. (2017)(what Manning, 2020, calls new classical monopsony) typically assume that workers always have a choice of the full set of employers but that jobs are imperfect substitutes.

However, there is a growing recognition of the importance of consideration sets in a number of areas of economics (e.g. see Goeree, 2008; Honka et al., 2019; Abaluck and Adams-Prassl, 2021; Dinerstein et al., 2018) The second section sets out a model of how the market power of firms is related to the size of the choice (consideration) set of workers. The third section applies this model of employer market power to a model of job search which encompasses the two existing approaches described above. Our model assumes job opportunities arrive occasionally but the consideration set may contain more than one option though not include all jobs in the market.

We start with a model where workers have idiosyncratic preferences over jobs, very similar to Card et al. (2017). The difference from these new classical monopsony models is that the worker's choice is not among the universe of available jobs but within their consideration set, a subset of the available jobs. While the implications for wage elasticity in the labor market remain fundamentally the same whether considering the universe of available jobs or a job seekers consideration set, a smaller consideration set increases the market share of each firm. Nonetheless, this distinction does not significantly alter the overall implications for wage elasticity.

We then add a layer of job search to the model: As in the modern monopsony models, workers get offers only occasionally and then have to choose whether to accept or not. In contrast to the workhorse model by Burdett and Mortensen (1998), we allow for jobseekers to receive not just one offer but a set of offers; this is again the consideration set. The worker now chooses among the jobs in the consideration set and decides which offer to accept or whether to stay in the current job (or unemployed, if the current status is unemployment). We show how market power depends on the intensity of job search, both on the extensive margin (the arrival rate of job opportunities) and the intensive margin (how many jobs they consider when they do search i.e. the size of their consideration set). An important feature is that the total arrival rate of job offers (i.e., all the consideration sets having arrived since the start of the job search) is not sufficient to measure employers' market power. For a given total number of offers, the market is more competitive if more of the offers arrive at once, i.e., if the consideration sets are larger.

We apply the findings of the model using job search data to obtain a novel measure of employer market power. We do so by taking a simple version of our model and showing that one can derive a statistic from the model that is very close to a Herfindahl Hirschman Index (HHI) and measures employer competition at the vacancy level. We start from the simplest version of this index where competition depends only on the sizes of consideration sets. We employ data on the job search behavior of UI recipients in Switzerland where we use 'clicks' from their use of the Swiss public employment service's 'job room' to define the extent of workers' consideration sets. Under strong assumptions, the size of the consideration set equals the number of vacancies a jobseeker views in a search session. We gradually build a more complex index, introducing consideration over multiple search sessions and heterogeneity in preferences over jobs in the consideration set. We show how different assumptions about the job search process affect our statistics of market power.

We further relate our index to commonly used measures of concentration ratios (e.g. Azar et al., 2020). These measures define a labor market as the combination of a location and an occupation. If a jobseeker also considers jobs outside of the occupation or location, this definition can underestimate the options a jobseeker has. Conversely, if jobseekers don't consider all jobs within the occupation-location cell, the measure can also overstate the number of options a jobseeker has. The measures are positively correlated with our index, however there are some notable differences. For instance, the agriculture, forestry, and fishing sector appears much less competitive when assessed using the HHI compared to our measure. This sector has fewer job openings; however, those seeking jobs often also explore opportunities in other fields.

Finally, we discuss the policy implications of our investigation of the relationship between job search and employer market power. One result of our model is that the competitiveness depends on the consideration sets of the average jobseeker interested in a firm. Thus an individual jobseeker does not have the incentive to search more to make the market more competitive since her contribution will only marginally affect the competitiveness[1]. This finding has implications for policies such as job search advice by the public employment services. If they can make jobseekers consider more options, this will have a positive impact on market competitiveness. However, this only holds true as long as those options are attractive enough to jobseekers. We provide some suggestive evidence that there is some scope to increase job search without lowering the quality of jobs considered.

We contribute to the strand of literature modeling monopsonistic labor markets (for an overview see Manning, 2020). A second contribution is adding to the strand of papers empirically measuring market power and outside options (Azar et al., 2020; Jäger et al., 2024; Caldwell and Danieli, 2024). Thirdly, we add to the discussion about a worker's relevant market when measuring the effects of employer concentration on wages (e.g. Azar et al., 2022b,a; Rinz, 2022; Schubert et al., 2024).

[1]This result is a consequence of the assumption that a firm has to set one wage for a position, i.e. cannot wage discriminate at the individual level.

Finally, we speak to the strand of literature designing interventions to broaden the unemployed's search scope with the aim to help them find employment (Altmann et al., 2018; Belot et al., 2019, 2022; Dhia et al., 2022; Altmann et al., 2022). We discuss how extending the search scope of jobseekers relates to labor market competition.

The plan of the paper is as follows. The next section outlines a model of employer choice by workers in a relatively abstract setting. The third section then considers an application of this framework to the modeling of job search. The fourth section shows how to apply this to the flow of recruits from unemployment, our empirical application. The fifth section describes our data. The sixth section uses this data to estimate measures of employer market power, investigating sensitivity to different assumptions and comparing to traditional concentration indices. Finally, we consider implications for whether job search is too little or too narrow to sustain competition in the labor market.

2 Worker Choice and Employer Market Power

2.1 Utility

Assume that the utility of individual i from working for firm f is given by:

$$v_{if} = \beta log W_f + \eta_{if} = \beta w_f + \eta_{if} \tag{1}$$

where W_f is the wage assumed to be posted by employer f (common to all workers)[2] and η_{if} is an idiosyncratic component. Assume the wage and idiosyncratic component are permanent characteristics so that jobs that offer higher utility now will always do. As is usual in discrete choice models, one can think of β as a measure of the extent of heterogeneity in the idiosyncratic component across firms; a higher β can be interpreted as lower heterogeneity in η. Assume η is independently identically distributed[3] across firms on some (possibly infinite) interval $[\eta_{min}, \eta_{max}]$, with a continuous log-concave density function $g(\eta)$ which implies the distribution function $G(\eta)$ is also log-concave (Bagnoli and Bergstrom, 2005). Log-concavity is often used to derive results in search models (e.g.Burdett, 1981; Manning, 2003). The most popular functional forms used for the distribution of the idiosyncratic component, e.g. extreme value, satisfy the log-concavity condition. If a worker has a choice of a set of firms $\mathcal{F}$ of firms (which we will refer to as the consideration set) the distribution function of the maximum utility, v, can be written as:

[2] The 'wage' could also be interpreted more generally to be any form of permanent vertical differentiation across firms as in Lamadon et al., 2022

[3] Though all results go through if the distributions are not identical, it just adds a lot of notation.

$$H(v;\mathcal{F}) = \Pi_{j\epsilon\mathcal{F}} G(v - \beta w_j) \tag{2}$$

Given the assumed log-concavity of $G(\eta)$, $H(v;\mathcal{F})$ will also be log-concave. Also assume there is always the option of being unemployed that offers utility:

$$v_{iu} = \beta log B + \eta_{iu} = \beta b + \eta_{iu} \tag{3}$$

where b is the log value of unemployment (in wage-equivalents). Assume η_u has a log-concave distribution function $G_u(\eta_u)$ independent of the idiosyncratic components in job utility. If the maximum utility from the available set of firms is v, the probability of being in employment is $G_u(v - \beta b)$.

2.2 The Supply of Labor to an Individual Firm

Consider workers who have a draw of idiosyncratic utility η from firm f so they have utility $\beta w_f + \eta$. These workers will acept this firm's offer if they have no better offer and and the offer is better than unemployment which happens with probability $H(\beta w_f + \eta; \mathcal{F}\backslash\{f\}) G_u(\beta(w_f - b) + \eta)$ where the notation $\mathcal{F}\backslash\{f\}$ denotes the set $\mathcal{F}$ excluding this firm f. As η has density $g(\eta)$ the probability of a worker choosing firm f from the set $\mathcal{F}$ can be written as:

$$n(w_f;\mathcal{F}) = \int_{\eta_{min}}^{\eta_{max}} g(\eta) H(\beta w_f + \eta; \mathcal{F}\backslash\{f\}) G_u(\beta(w_f - b) + \eta) d\eta \tag{4}$$

As long as β is finite (however large) labor supply will be a continuous function of the wage. The case where jobs are perfect substitutes is, however, different. In this case the labor supply will be the discontinuous max function. A number of properties of $n(w_f;\mathcal{F})$ are useful for later.

Proposition 1. $n(w_f;\mathcal{F})$ is:

1. $n(w_f;\mathcal{F})$ *is* increasing in the offered wage w_f
2. The elasticity of $n(w_f;\mathcal{F})$ with respect to the wage w_f is decreasing in w_f
3. Adding an extra firm to the set $\mathcal{F}$ which is chosen with a probability that depends on w_f reduces the elasticity of $n(w_f;\mathcal{F})$ with respect to the wage w_f

Proof. See Appendix 8.1. □

Proposition 1.1 simply says that as the wage rises, workers are more likely to choose it over other firms and unemployment. Proposition 1.2 tells us that the market power of employers as measured by the wage elasticity of employment increases as the wage increases. This will have important implications later. Finally, Proposition 1.3 formalizes the notion that that the labor market for an individual firm is more competitive if workers have a choice of more employers (though only those where the probability of choosing the extra job depends on the wage offered by this one); this is very intuitive. One situation in which an extra firm does not change the competitiveness of the market is if the extra job is never chosen by the worker; adding irrelevant jobs makes no difference to the labor supply elasticity as would be expected.

2.3 Employer Market Power as the Choice Set Becomes Large

We think of a competitive labor market as one in which a worker has lots of options. But does employer market power go to zero as the number of choices goes to infinity? To address this question in the context of a symmetric equilibrium we consider the case where a worker has C options all of which pay the same wage in equilibrium (though the chosen wage has to be optimal from an individual firm perspective). To keep things simple we also assume that workers always prefer employment to unemployment so that $G_u() = 1$.

Proposition 2. *In a symmetric equilibrium where employment is always prefered to unemployment:*

1. the elasticity of labor supply to an individual firm can be written as*:*

$$\epsilon = \beta \left[C g(\eta_{max}) - \frac{g'(\eta_{max})}{g(\eta_{max})} + \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)} \right]' G(\eta)^C \, d\eta \right] \tag{5}$$

2. The elasticity is an increasing, concave function of C if $g(\eta)$ is log-concave.

3. A necessary and sufficient condition for the elasticity to become infinite as $C \to \infty$ is that $g(\eta_{max}) > 0$

Proof. See Appendix 8.2. □

The necessary and sufficient condition for the elasticity to be finite even as the choice set becomes very large is that the density of the best possible value of the idiosyncratic component of utility is zero (Berry and Pakes, 2007, make a similar point). Intuitively, with a non-zero probability of the best draw of the idiosyncratic component the distribution of the gap between the first- and second-best values of the idiosyncratic component collapses to zero as $C \to \infty$ in which case the worker's choice simply comes down to the wage. A model with the property that $g\left(\eta_{max}\right)>0$ is Bhaskar and To (1999) who assume that workers and firms are uniformly distributed on the edge of a circle. In this case the maximum value of the idiosyncratic component corresponds to a 'distance' of zero. But the idiosyncratic component can be bounded above and the limit of the elasticity still be finite. An example is if firms and workers lived on a uniform featureless plain so that the number of firms increases with the distance instead of being uniform; the set of firms rises with the distance from the worker's location. And if, as seems plausible, the idiosyncratic component is really the sum of lots of small individual components then one would expect that the probability of them all taking their maximum value is vanishingly small. The popular MNL model has the feature that η is unbounded above with a density which then has to go to zero. In this case the second term in (5) is 1 and the final term is $-\frac{1}{C}$ [4] leading to the familiar expression for the elasticity $\beta\left[1-\frac{1}{C}\right]$. C can be thought of as infinite in the case where each firm is assumed infinitesimal in relation to the market (Card et al., 2017; Lamadon et al., 2022) but finite when the number of firms is assumed finite (Berger et al., 2022; Jarosch et al., 2019). The term $1/C$ is the first place where one can see a connection to traditional concetration indices as this is the value of the HHI index when firms are of equal size.

3 Job Search

The previous section was about labor supply of workers conditional on a choice set, and job search is essentially a model for the determination of the consideration set and how it changes. This section applies the set-up of the previous section to model job search in a way that allows a wider range of possibilities than most of the literature. In the new classical monopsony tradition (e.g. Card et al., 2017), the most common assumption is that all firms are in the choice set, $\mathcal{F}$ but that the jobs are imperfect substitutes; these models are typically static but if all jobs are always available any time dimension is irrelevant because workers can optimise period by period. In contrast, search models (e.g. Burdett and Mortensen, 1998) assume the consideration set is very restricted, that there is one alternative firm in addition to the current firm (if the worker is currently employed). Often these models assume jobs are perfect substitutes ($\beta=\infty$ in our notation). Our set-up aims to encompass both traditions.

Assume that both employed and unemployed workers receive opportunities to get or change jobs at a rate λ; this means that the reservation utility level will be the utility from unemployment

[4] because $\left[\frac{g'(\eta)}{g(\eta)}\right]'=-\frac{g}{G}$ in this case

as accepting or refusing a job has no consequences for future job opportunities[5]. With one eye on the empirical application we refer to an opportunity to change jobs as a 'session'. Assume δ is the exogenous job destruction rate. With the assumption that the idiosycratic component is fixed, no worker would ever want to quit to unemployment even if the unemployed sometimes refuse jobs.

Also assume that when the worker has the opportunity to get or change jobs they have a choice of a set of firms C other firms chosen at random (this is the size of their consideration set). In terms of (4) this means that the set $\mathcal{F}$ has cardinality C if the worker is currently unemployed and $C+1$ if currently employed (i.e. the worker can choose to remain at the existing firm[6]. The usual search model has $C=1$.

3.1 The Labor Supply to a Firm

To derive the extent of employer market power we need the wage elasticity of the labor supply curve to a firm that pays a certain wage. This can be derived from (4) if we take account of the endogeneity of the set $\mathcal{F}$. A useful trick given our assumptions is the following. Whenever workers become unemployed, all previous job opportunities become void; the worker is forced to start the process of finding a good job again. Index by x the number of sessions the worker has had to take or change jobs since last becoming unemployed. Denote by $\phi(x)$ the fraction of workers at every point in time who have had x opportunities. Appendix 8.4 shows that this is given by:

$$\phi(x) = \left(\frac{\lambda}{\delta+\lambda}\right)^x \phi(0) = \left(\frac{\lambda}{\delta+\lambda}\right)^x \frac{\delta}{\delta+\lambda} \tag{6}$$

To keep things simple assume that the overall set of firms is so large that a firm is never sampled twice. Then a worker who has had x sessions will have sampled Cx jobs; denote this set by $\mathcal{F}(x)$. From these jobs, the worker will take the best option (which might be unemployment) and the choice will be given by (4). The order that these jobs will have been received in does not matter; the worker will currently have the best option.

An individual firm will hire a worker who has had $x\,(>0)$ sessions if they are one of the firms being considered (this happens with probability equal to Cx/F) and if they are the best option. Using (4) this means that labor supply to a firm that pays w_f will be given by:

$$N_f(w_f, ..) = C\frac{L}{F}\sum_{x=1}^{\infty}\phi(x)\, xE\left[n\left(w_f; \mathcal{F}(x)\right)\right] \tag{7}$$

[5] This is just to keep things simple to clarify the key ideas; one can generalize to the case where job offer arrival rates are different for the employment and unemployed

[6] One could treat the number of jobs in the consideration set as stochastic; this adds notation for little insight

where the expectation is over the set of other job offers that the worker has received in x sessions. We assume that the distribution of other job offers is independent of what this firm pays so is treated as exogenous from the perspective of the individual firm. $N_f(w_f,..)$ is log-concave in the offered wages as it is a linear function of the log-concave functions $n(w_f;\mathcal{F})$ (proved in Proposition 1); this has the implication that the firm as a wage elasticity of labor supply curve that is, ceteris paribus, decreasing in the own wage.

The firm will choose the wage to maximize profits $\pi(w_f) = (P - W_f) N_f(w_f,..)$. As labor supply is log-concave, the profit function will be strictly log-concave which implies a unique choice of the wage however the distribution of wage offers is drawn. As usual, the first-order condition is:

$$\frac{W_f}{P - W_f} = \frac{\partial log N_f(w_f,..)}{\partial w_f} \tag{8}$$

The left-hand side of (8) is increasing in the wage and the right-hand side decreasing, another way of showing the optimal wage must be unique. One implication of the uniqueness of the optimal wage is that if firms are homogeneous and the way that wage offers are drawn the same for all of them, then the equilibrium must be a single wage. This shows that the equilibrium wage dispersion result of Burdett and Mortensen (1998) is a knife-edge result deriving from the assumption that all jobs are perfect substitutes. If jobs are perfect substitutes the choice model (4) becomes a max function and labor supply discontinuous in the offered wage at any wage where there is a mass point of other wages. Intutively, if there is a mass point of wages at one point, a firm can always increase proftis by offering an infinitesimally higher wage as profit per worker hardly changes but the number of workers rises discontinuosuly. But as soon as β is finite, however high, this argument for equilibrium wage dispersion breaks down though others (based on employer heterogeneity) remain.

3.2 The determinants of employer market power

(8) says that wages will be lower the lower is the wage elasticity of labor supply to the employer. From (7) this can be written as:

$$\frac{\partial log N_f(w_f,..)}{\partial w_f} = \frac{\sum_{x=1}^{\infty} \phi(x)\, x E\left[n(w_f;\mathcal{F}(x))\, \frac{\partial log n\left(w_f;\mathcal{F}(x)\right)}{\partial w_f}\right]}{\sum_{x=1}^{\infty} \phi(x)\, x E\left[n(w_f;\mathcal{F}(x))\right]} \tag{9}$$

The following Proposition provides some results on how market power is affected by parameters of the model

Proposition 3. Employer market power is decreasing in:

1. λ/δ the arrival rate of job opportunities relative to the job destruction rate

2. C the number of alternatives considered at each opportunity;

Proof. See Appendix 8.3. □

These results can be related to existing measures of the competitiveness of labor markets. For example, λ/δ is used as a measure of monopsony power in Burdett and Mortensen (1998). And the number of firms in the consideration set, C, affects market share in the popular MNL model (e.g. see Card et al. (2017). It is also related to the concentration measure which, in the case of identical employers is given by $1/C$. One other parameter that might be expected to reduce market power is β which measures the extent to which employers are close substitutes for each other and importance of idiosyncracy; this is the classic measure of monopsony power in the new classical literature. But there can be individual firms where an increase in β raises market power; e.g. in the MNL model if this firm is a low-wage firm, then an increase in β lowers market share which tends to off-set the direct effect. However, averaged across all firms, one would expect that an increase in β reduces employer market power.

One feature of (9) is that the total arrival rate of job offers λC is not sufficient to measure the market power of employers. To see this, consider a special case in which we have an MNL structure and employment is always preferred to unemployment. In this case, in a symmetric equilibrium (9) will become:

$$\frac{\partial logN_f\left(w_f,..\right)}{\partial w_f}=\beta\left[1-\frac{\delta}{\lambda C}\sum_{x=1}^{\infty}\left(\frac{\lambda}{\delta+\lambda}\right)^x\frac{1}{x}\right] \tag{10}$$

For a given level of λC (10) shows that the market power of employers will be increasing in λ. An implication is that labor markets will be more competitive if workers are considering many offers simultaneously rather fewer offers arriving more frequently. The intutition for this can understood by thinknig about a static model in which workers have a one-shot choice over a set of employers. If all workers have a choice of 5 employers the extent of competition will be given by the level associated with this choice set. Now imagine replacing this with a situation in which half the workers have no offers and half have 10 so the expected number of offers is the same. The workers with no offers are in a bad situation but they contribute nothing to the level of competition. That will be determined by those who do have offers and because all of these now have 10 offers the market will be more competitive.

4 The Elasticity of the Flow of Recruits from Unemployment

The discussion so far has been about the wage elasticity of the labor supply to the firm as a whole. But our empirical application is about the flow of recruits from unemployment and the elasticity formulae for market power will be different for this (or any other) group because their labor supply elasticity may differ. The next section presents an application of a 'bottom up' approach to measuring employer market power which builds firm-level labor supply elasticities from the individual level. We then use this approach to estimate the wage elasticity of an individual unemployed worker to firms in their consideration set and then aggregate these individual-level elasticities to estimate elasticities to the vacancy level.

4.1 A Bottom-Up Approach to Measuring Labor Supply Elasticities

We normally think of the labor supply elasticity at firm-level because this will determine the mark-down of wages from marginal products. This section shows how one can construct a 'bottom-up' version from labor supply elasticities at individual level. This offers the advantage that individual-level rather than firm-level elasticities may sometimes (as in this paper) be easier to estimate. Suppose that the probability of individual i from working for firm f is given by $\theta_{if}\left(W_f,.\right)$ i.e. depends on the offered wage, W_f,but also on other stuff that we do not need to specify. From this function we can derive the elasticity of labor supply of individual i to firm f as:

$$\varepsilon_{if}\left(W_f,.\right) = \frac{\partial log\theta_{if}\left(W_f,.\right)}{\partial logW_f} \tag{11}$$

If each firm could individualize the wage (i.e. act as a discriminating monopsonist separately for every worker) $\varepsilon_{if}\left(W_f,.\right)$ would be relevant for the mark-down that worker i would have; this would be relevant if the firm individualized wages. Where wages cannot be individualized a weighted average of the individual-level elasticities will be relevant. For example, in the simplest case where the firm cannot wage discriminate (i.e. pays the same wage to all its workers) the supply of labor to firm f is $\sum_j \theta_{jf}\left(W_f,.\right)$ so that the elasticity of labor supply to firm f can be written as:

$$\varepsilon_{f}\left(W_f,.\right) = \frac{\sum_j \theta_{jf}\left(W_f,.\right)\varepsilon_{jf}\left(W_f,.\right)}{\sum_j \theta_{jf}\left(W_f,.\right)} \tag{12}$$

i.e. a weighted average of the individual elasticities with the weights given by the probability of the worker working for the firm[7]. (12) shows how measures of market power at the individual level

[7] 12 seems undefined if $\theta_{if}\left(W_f,.\right) = 0$ but this does not matter as a worker that has no probability of working at a firm is irrelevant to its market of power. An alternative way of writing the firm-level elasticity is $\varepsilon_f\left(W_f,.\right) =$

can be used to inform market power at the firm level. We can also derive the average elasticity experienced by individual i; this will be given by:

$$\sum_{f} \theta_{if}\left(W_f,.\right) \varepsilon_f\left(W_f,.\right) = \sum_{i,j} \theta_{if}\left(W_f,.\right) \theta_{jf}\left(W_f,.\right) \varepsilon_{jf}\left(W_f,.\right) \tag{13}$$

Note that the competitiveness of the labor market facing an individual depends on the elasticity of labor supply not primarily of themselves but the elasticity of those workers with whom they tend to work. A worker with very inelastic labor supply will be in a competitive labor market if they tend to work with very mobile workers while a very mobile worker will find they are highly exploited if they tend to work with very immobile workers. One implication of (13) is that workers may have a weak incentive to maintain the competitiveness of labor markets through their job search as the benefits of increased labor market competition largely flow to others; the final section discusses the possible implications of this. In this paper we use the bottom-up approach applied to the unemployed. The next section considers the elasticity of their labor supply.

4.2 The wage elasticity of the labor supply of the unemployed

Consider an individual unemployed worker, i; they will have a particular, fixed value of unemployment given by $\beta b + \eta_{ui}$. The probability of this worker choosing firm f from the set $\mathcal{F}$ can, by analogy to (4), be written as:

$$\theta_i\left(w_f; \mathcal{F}\right) = \int_{\beta\left(w_f - b\right) + \eta_{ui}}^{\eta_{max}} g\left(\eta\right) H\left(\beta w_f + \eta; \mathcal{F} \backslash \left\{f\right\}\right) d\eta \tag{14}$$

For a given assumption about the distribution of the idiosyncratic shocks this formula can then be used to derive the labor supply elasticity. We will use a common, simple functional form, namely that the choice between the different options and unemployment has a MNL form in which case (14) can be written as:

$$\theta_i\left(w_f; \mathcal{F}\right) = \frac{e^{\beta w_f}}{e^{\beta b + \eta_{ui}} + \sum_{j \epsilon \mathcal{F}_i} e^{\beta w_j}} = \frac{\sum_{j \epsilon \mathcal{F}_i} e^{\beta w_j}}{e^{\beta b + \eta_{ui}} + \sum_{j \epsilon \mathcal{F}_i} e^{\beta w_j}} \frac{e^{\beta w_f}}{\sum_{j \epsilon \mathcal{F}_i} e^{\beta w_j}} = \rho_i\left(w_f; \mathcal{F}\right) s_i\left(w_f; \mathcal{F}\right) \tag{15}$$

The last two terms write the probability of choosing an individual firm as the probability of choosing any firm (i.e. leaving unemployment) times the probability of choosing this firm conditional on leaving unemployment. Differentiating (15), the wage elasticity can then be written as:

$\dfrac{\sum_j \frac{\partial \theta_{jf}\left(W_f,.\right)}{\partial log W_f}}{\sum_j \theta_{jf}\left(W_f,.\right)}$ which makes this clear.

$$\epsilon_{if} = \frac{\partial log\theta_i\left(w_f;\mathcal{F}\right)}{\partial w_f} = \frac{\partial log\rho_i\left(w_f;\mathcal{F}\right)}{\partial w_f} + \frac{\partial logs_i\left(w_f;\mathcal{F}\right)}{\partial w_f} = \beta\left[\left(1-\rho_i\right)s_i + 1 - s_i\left(w_f;\mathcal{F}\right)\right] \tag{16}$$

In what follows, we, for the moment, assume that workers always choose employment over unemployment. Relaxing this is to come. The the elasticity at the firm level will be given by:

$$\varepsilon_f = \beta\frac{\sum_i \theta_i\left(w_f;\mathcal{F}\right)\left[1-\theta_i\left(w_f;\mathcal{F}\right)\right]}{\sum_i \theta_i\left(w_f;\mathcal{F}\right)} = \beta\left[1-\frac{\sum_i \theta_i\left(w_f;\mathcal{F}\right)^2}{\sum_i \theta_i\left(w_f;\mathcal{F}\right)}\right] \tag{17}$$

where the summation is over individuals who have firm f in their consideration set. In what follows we provide estimates of the second term in square brackets which is relevant to employer market power. We do not estimate β though that is important for a full assessment of employer market power (and may be the more important factor). The second term has affinities to HHI indices because it involves sums of squared shares. For this reason we refer to them as concentration indices. But the way in which the employment shares enter our concentration indices is a bit different. A standard HHI measure uses the shares of the firm in employment or vacancies. In contrast, ours starts from the individual level and then averages over the individuals who have this firm in their choice set. We now turn to our empirical implementation.

5 Data

Our main data source is the activities of unemployed job-searchers using the 'job room' of the Swiss public employment service (`https://job-room.ch/home/jobseeker`), available in German, French, Italian, and, conveniently for many of us, English. The vacancies in the job room are both directly posted there and scraped from other locations; the claim is that it has the universe of job vacancies in Switzerland though, in practice it is unlikely to have 100% coverage. Even if all vacancies are in the job room, they will often also be posted elsewhere; later we discuss how we deal with the fact that we only observe a fraction of the job search activity of our sample.

When looking for vacancies in the job room the front screen looks like Figure 1, asking for occupation/category, competencies/skills and canton/work location. After filling some or all of these categories the jobseeker is presented with a range of available vacancies. For example, after a search of occupation "Office managers" in "Zurich", the jobseeker sees a set of vacancies like those shown in Figure 2 . To find out more about these vacancies (and possibly to apply for them through the portal) the jobseeker needs to 'click' on them and it is these clicks that are the basic data we use as a measure of jobs that are being considered by the jobseeker. There are few existing studies using click data - though probably more coming. Faberman and Kudlyak, 2019 investigate how

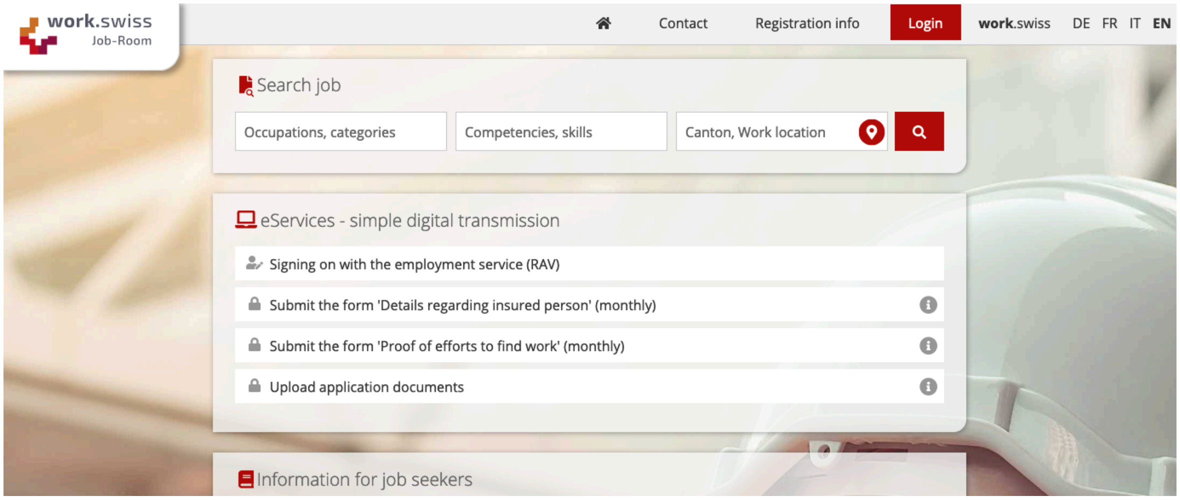

Figure 1: Screenshot from `https://job-room.ch/home/jobseeker`. Screenshot taken 10-02-2023.

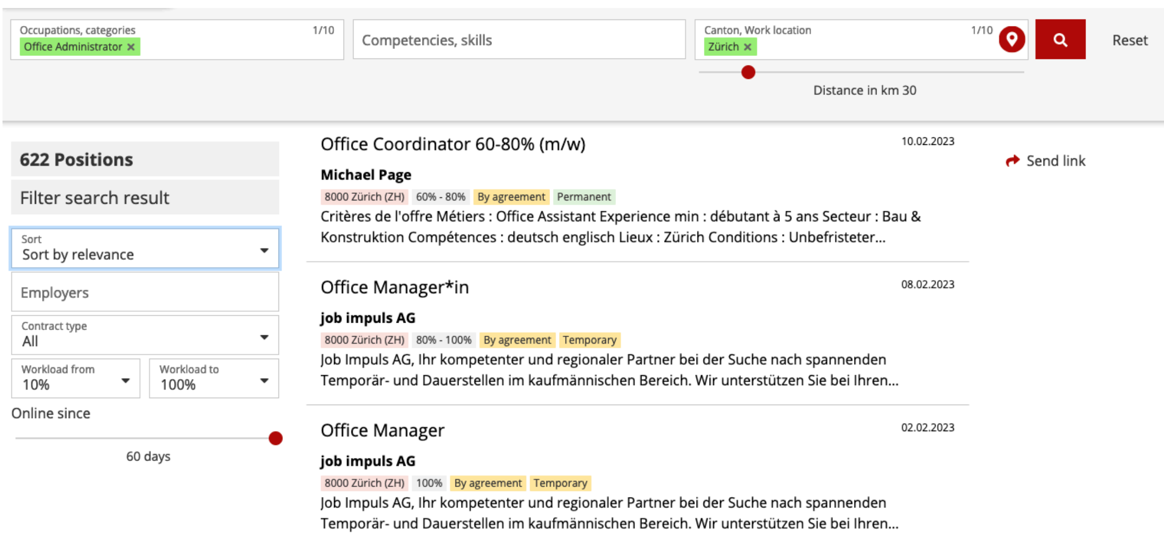

Figure 2: Screenshot of the result list when searching for "Office managers" in Zurich on the job room (`https://job-room.ch/home/jobseeker`). Screenshot taken 10-02-2023.

search intensity using clicks varies with search duration, Adrjan and Lydon, 2019 show that clicks correlate with other measures of labor market tightness and Hensvik et al., 2021 investigate how search behavior changed during the pandemic. Klaeui et al. (2024) look at click data to explore the occupational scope of recruiters and jobseekers and to test whether they adapt the scope to changing labor market circumstances. Klaeui (2024) uses clicks as a measure of job consideration and analyzes jobseekers' individual consideration scope and its interplay with the jobseekers' ability to benefit from job openings by finding employment.

Our use of clicks data to define the consideration set deserves some discussion. One can think of it as representing some degree of interest between simple awareness of a job vacancy and an application (which have been studied elsewhere e.g. Banfi and Villena-Roldn, 2019 Azar et al., 2022a). All of these measures are of some interest but none are perfect. 'Awareness' has the obvious problem that it is hard to measure but awareness of a job that a searcher has no interest in or no chance of getting does nothing to make the labor market more competitive (as Proposition 1.3 showed). A click suggests some minimal level of interest in the job. At the other end, an application represents more serious interest but perhaps goes too far in the other direction; one might think that labor markets are more competitive if there are more jobs of interest to a searcher even if they only apply for a few of them ex post. For example, if information on the vacancy is sufficient to determine the optimal job, and all applications led to a job offer, one would only ever see one job application (to the desired job) but this would be misleading about the extent of labor market competition.

While the job room can be used by anyone, our sample is of unemployed jobseekers who are claiming UI. We have all the clicks from registered unemployed in the window 06-06-2020 - 30-06-2021. This is during the pandemic in which unemployment in Switzerland rose from 4% to 5.6% and our findings may apply only to that period. A sample of the registered unemployed has the advantage that we observe some characteristics about them, including their previous jobs and the future job (if any). This is also a group of jobseekers who are encouraged to use the job room although they are not required to. A condition of UI receipt is evidence of job search and using the job room is an easy way to provide evidence of search so we would expect many of the unemployed to use it. Nonetheless, there are other sources of information about vacancies and we do not observe this; we are only observing a sub-set of job search. Later we discuss how we deal with this issue.

318,114 unemployment spells start within the window in which we have the click data. A small proportion of individuals have more than one spell overlapping the window, such that in total the 318 114 spells correspond to 294 823 individuals. When we exclude jobseekers with incomplete education, residence, or prior earnings information, the sample is 285,033 spells. 45% have created a login for the job room, and at least one click is made in 30% of spells. We further exclude jobseekers who seem to be on temporary lay-offs, i.e. where the pre- and post-unemployment job is the same (this being a feature, for example, of seasonal work in construction (Liechti et al., 2020)). Our final sample is 81,006 unemployed job seekers with at least one click on the platform; Table 1 presents some descriptive statistics and compares the sample to the population of registered unemployed.

The main way in which our sample of unemployment spells differs from all spells is that it is better-educated and, reflecting that, has a higher level of insured earnings.

We divide the way job seekers use the job room into sessions and the number of clicks per

	Sample (N = 81 006)			All spells (N = 285 033)			Difference	
	Mean	Min	Max	Mean	Min	Max	Difference	p-Value
Female	0.51	0.00	1.00	0.46	0.00	1.00	0.06	0
Age (at registration)	38.77	18.00	68.12	38.06	18.00	71.04	0.71	0
Primary education	0.20	0.00	1.00	0.30	0.00	1.00	-0.09	0
Secondary or vocational educ.	0.56	0.00	1.00	0.53	0.00	1.00	0.03	0
University education	0.24	0.00	1.00	0.17	0.00	1.00	0.07	0
Non-permanent resident	0.19	0.00	1.00	0.22	0.00	1.00	-0.03	0
> 3 years tenure in last job	0.66	0.00	1.00	0.63	0.00	1.00	0.03	0
Insured earnings (CHF)	4554.40	0.00	12350.00	3982.06	0.00	12350.00	572.34	0
Spell duration (months)	6.81	0.03	23.50	5.26	0.03	23.50	1.55	0

Table 1: Descriptive statistics on the characteristics of the jobseekers in our sample. The sample is compared to the characteristics of the population of registered jobseekers whose spells start within the period in which clicks on Job Room are recorded (06-06-2020 - 30-06-2021)

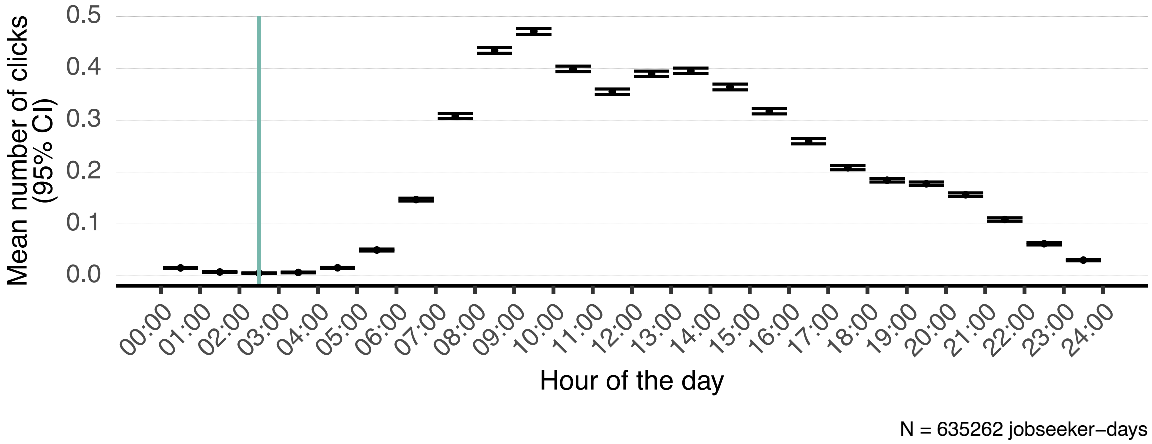

Figure 3: Number of clicks by time of the day. Averages over jobseekers.

session. We interpret a session as being an opportunity to consider a set of jobs (x in the stylized model above) and the number of clicks per session to be the size of the consideration set (C in the model above). We define a session to be a day in which there is at least one click. Assuming sessions never last more than a day and there is never more than one session per day seems reasonable due to the following. Figure 3 shows the distribution of the total number of clicks by time of day; unsurprisingly, there are very few in the middle of the night. For this reason, we assume 'days' start at 2:30am.

To justify assuming at most one session per day, define sessions on the same day as different when the interval between clicks exceeds z hours. For example, if a jobseeker has one session in the morning and another in the evening, this would show up as an interval of 6+ hours between clicks. As we vary the time interval Figure 4 shows that the average number of sessions is not much above 1 until we come to implausibly short intervals such as 15 minutes.

We disregard all clicks made before registration and after deregistration at the employment

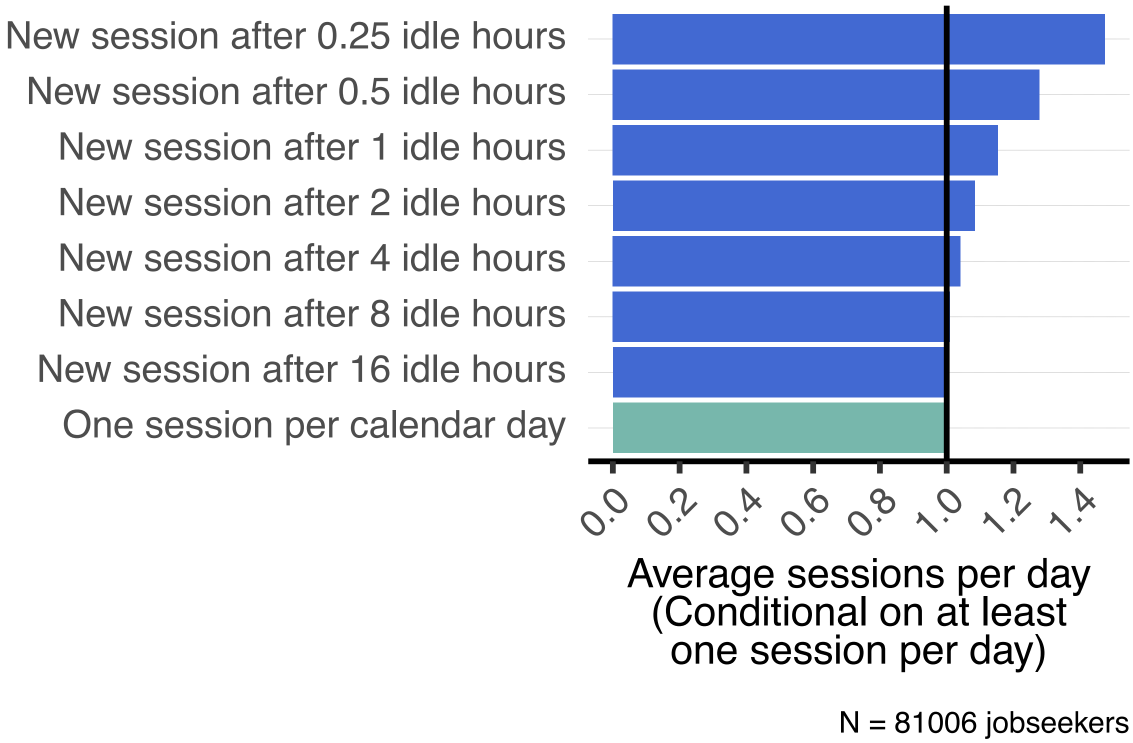

Figure 4: Number of sessions per day with different definitions of a session. Averages over jobseekers.

agency (those clicks account for approximately 0.4% of total clicks). If an ad is clicked twice during the same day, we consider this as one click[8]. Clicks on the same ad in two distinct sessions are counted separately. Using this definition of a session Figure 5 shows the distribution of the number of sessions per month.

The mean is 1.94 i.e. the average job seeker is using the job room every two weeks. Figure 6 shows the distribution of the number of clicks per session. The mean is 4.9 but the long right tail means the median is 3. This is quite a low level of search activity, suggesting that observed worker consideration sets are quite small; this will have implications for our measures of employer market power. However, it should be borne in mind that we only observe part of job search. For context Krueger and Mueller (2011) report that their sample of the unemployed in New Jersey spent an average of 98 minutes a day on job search, DellaVigna et al. (2022) report 81 minutes per day.

There is, of course, systematic variation in the extent of search activity across individuals and, for the same individual, over the course of an unemployment spell. This is not our main focus of interest, so we do not discuss it in the main text. But Appendix C shows that search activity tends

[8]Most of those clicks are from the same minute, suggesting that they are attributable to technical issues rather than specific search behaviour.

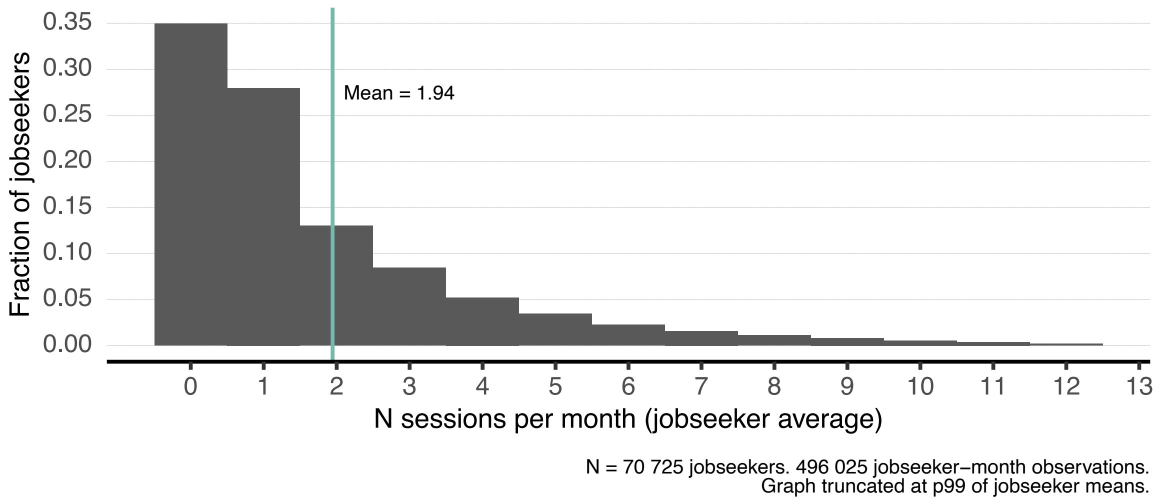

Figure 5: Distribution of the number of sessions per month. Averages over jobseekers.

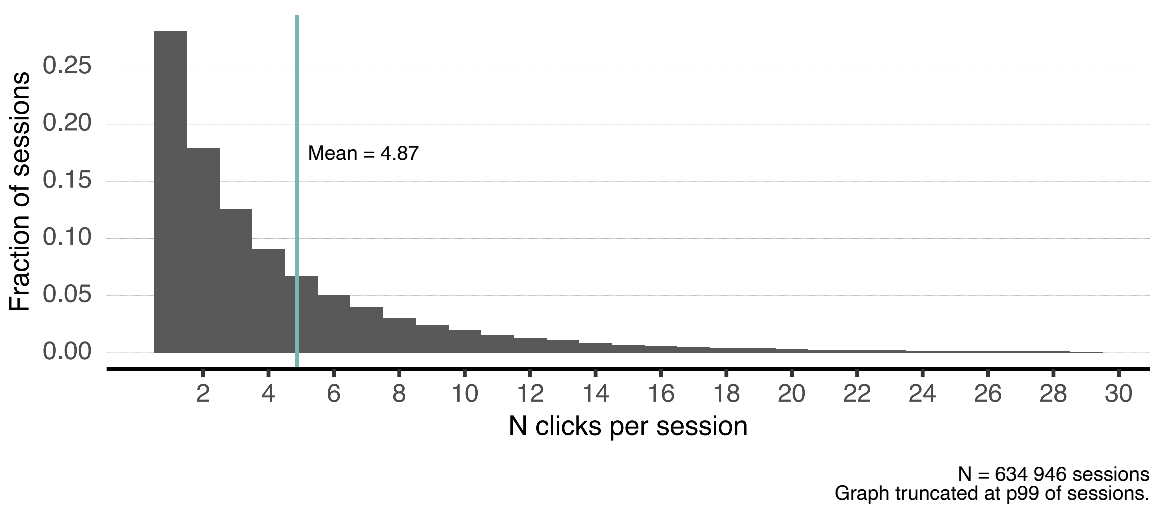

Figure 6: Distribution of the number of clicks per session.

to fall over the course of a spell, consistent with other studies e.g. Faberman and Kudlyak, 2019 and Hensvik et al., 2021.

6 Estimates of Employer Market Power

6.1 Methods

We start our analysis assuming that all vacancies receiving clicks are equally attractive in the eyes of workers; think of them as all having the same 'wage', w, so the systematic part of utility is the same in all jobs. In this case labor supply (15) can be written as:

$$\theta_i\left(w_f;\mathcal{F}\right)=\left(\frac{1}{\gamma_i+C_i}\right) \tag{18}$$

where $\gamma_i = e^{\beta(b-w)+\eta_{ui}}$ is a measure of the attractiveness of unemployment relative to work and C_i is the size of the consideration set. Further, assume that $\gamma_i = 0$ which corresponds to the case where all jobs are more attractive than unemployment. These are simplifying assumptions but they require little information beyond the number of clicks and, as we shall see, facilitates comparison with concentration indices which have been widely used in the literature (Azar et al., 2020, 2022b). With this assumption the elasticity at the vacancy level (16) can be written as:

$$\varepsilon_f=\beta\left[1-\frac{\sum_i\left(\frac{1}{C_i}\right)^2}{\sum_i\left(\frac{1}{C_i}\right)}\right] \tag{19}$$

where the summation is over consideration sets containing firm f. 19 shows that β is important for market power but we do not seek to estimate that here; our interest is in the magnitude of the second term in the square brackets. We refer to this as a concentration index because it has similarities to HHI measures of concentration that have been widely used in the literature. An alternative way of writing (19) is:

$$\varepsilon_f=\beta\left[1-E\left(\frac{1}{C_i}\right)-\frac{Var\left(\frac{1}{C_i}\right)}{E\left(\frac{1}{C_i}\right)}\right] \tag{20}$$

where the expectations and variances are over the jobseekers who click on this firm. This equation shows that the average number of the reciprocal of the number of clicks matters but also the variance. For a given mean, higher variance implies more market power. In a further special case where all workers have the same size of consideration set, (19) reduces to:

$$\varepsilon_f = \beta \left[1 - \frac{1}{C} \right] \tag{21}$$

Note the second term in square brackets in 21 is the value of the concentration index for equally-sized firms.

Our different measures of employer market power are based on different assumptions about how we measure the size of the consideration sets.

6.2 Baseline Estimates

Our first estimate treats each session as a separate consideration set. This is the approach one would take on a literal reading of the model presented above and with many theoretical models in which all jobs in the current consideration set are available to the workers if they want, they are available immediately and if not taken now, they are no longer available. In each session the unemployed worker has a set of vacancies to consider. If any are better than unemployment the spell ends and the individual disappears from our data set. If none are better then unemployment then the individual remains in our data set but the jobs from this and previous sessions are irrelevant for future consideration because they are worse than unemployment. Each consideration set has a 'now or never' feature. Figure 7 computes the index using this assumption. We only compute this for vacancies with clicks from at least 10 jobseekers as the estimate of the variance will be too low for vacancies clicked on by few workers (see 20). The measured market concentration is very high, the average index value is 4195 which is equivalent to a market of 2.4 recruiting firms with equal market shares.

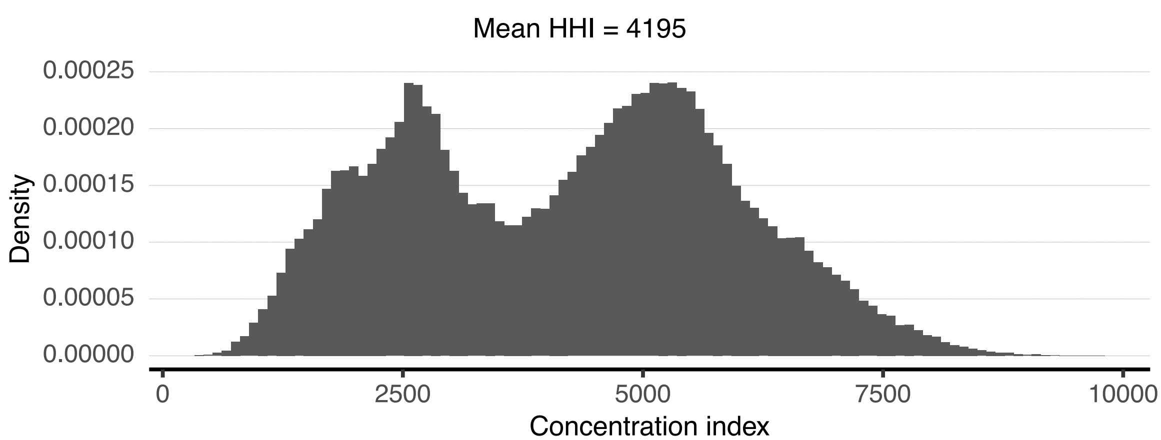

Figure 7: Distribution of the HHI based on Equation 19 over vacancy postings with clicks from more than 10 jobseekers. To compute the HHI, each session is regarded as a separate consideration set.

If every session is separate, the fact that we do not observe sessions outside the job room does not matter under the assumption that, on average, they are the same.

6.3 A Comparison with Concentration Indices

Our measures of the extent of employer market power can be compared to measures of labor market concentration (of vacancies or employment) that have become popular in recent years following the work of Azar et al. (2020) and have been shown for a number of countries to be correlated with wages (e.g. Rinz, 2022). These studies typically define a labor market and then compute HHI for them. Azar et al. (2020) define a labor market as a 6-digit SOC occupation in a commuting zone for a particular period. We can compare these measures with ours. Compared with HHI our measures suggest i) less competition because not all jobs in a labor market are being clicked on, but ii) more competition because we do not impose restrictions that job search is restricted to a specific occupation or area, so markets are wider. Table 2 shows that many jobseekers click on a variety of occupations [9] and in a variety of commuting zones.

Share of clicks (%) in the mode of	Mean	p25	Median	p75
ISCO-08 4-digit	48.1	26.9	43.8	66.7
ISCO-08 3-digit	49.8	28.6	45.7	69.2
ISCO-08 2-digit	53.0	32.9	50.0	72.0
ISCO-08 1-digit	63.0	44.9	61.3	81.8
Commuting zone	76.4	59.8	81.5	95.7

Table 2: Search across market boundaries. For every jobseeker the share of clicks inside the cell with most clicks is computed. The table shows the distribution of the share over jobseekers with 10 or more clicks.

Figure 8 shows that concentration indices are much higher when computed using our measures than when computed using all vacancies in a labor market. However they have a positive correlation of 0.26 (cells weighted by the number of vacancies).

Figure 9 shows how our measure and the HHI varies over broad occupation categories and regional characteristics.

In general, the patterns of variation are similar but there are some differences. The intercept for our measure is much higher reflecting the generally lower level of competition we find. Labor markets in major cities are more competitive but the extent is smaller in our measure; there are many more vacancies in these areas so the HHI is lower but the number of clicks rises less than proportionally to the number of vacancies. And the labor market for workers in agriculture, forestry

[9] though Hensvik et al., 2021 find for Sweden that job search was wider in the pandemic so it is possible our findings are not normal.

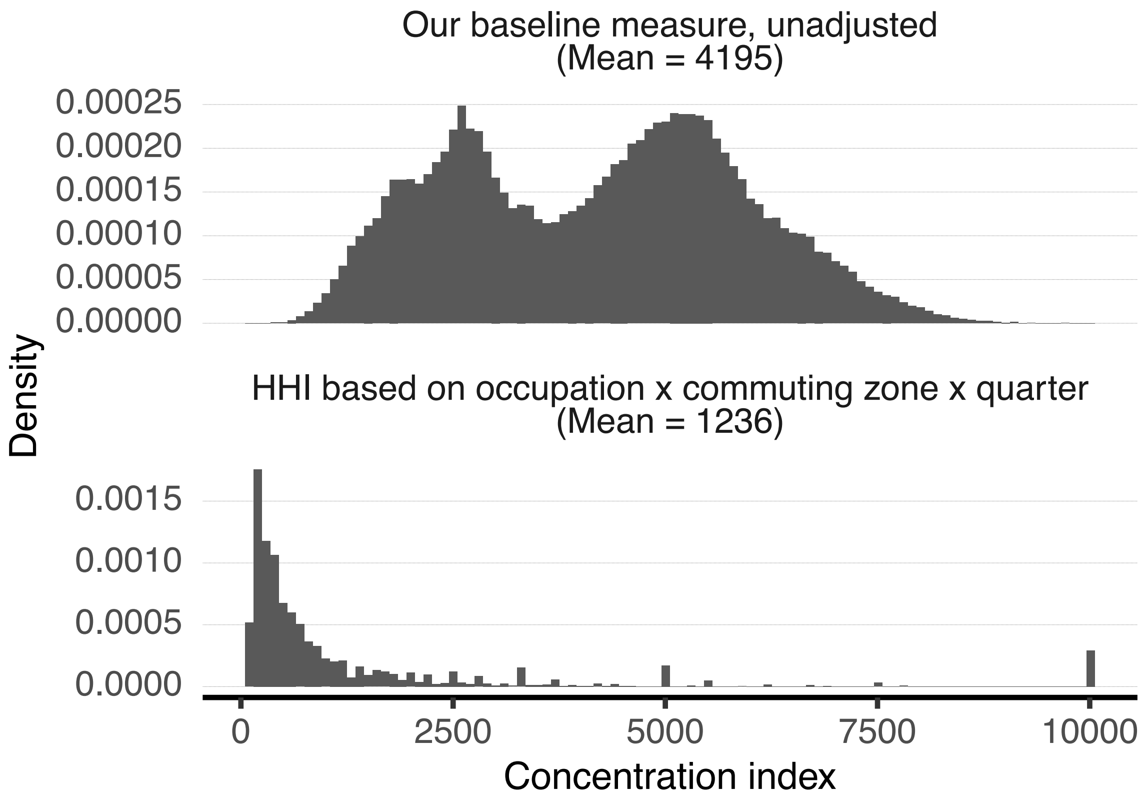

Figure 8: Distribution of the HHI based on Equation 19 over vacancy postings. To compute the HHI, each session is regarded as a separate consideration set.

and fishing is estimated to be much less competitive using the HHI as compared to our measure; there are few vacancies in this sector but the jobseekers clicking on them are often clicking on vacancies in other occupations.

Our concentration measure is at vacancy level so we also have within-market dispersion. Figure 10 shows how concentration varies across vacancies within the traditional definition of a market. On our measure, jobs with a permanent position, an immediate start and part-time generally have higher levels of concentration.

Our estimates of competition in this section have been based on the assumption that sessions can be treated separately. We next investigate the sensitivity of our conclusions to making a number of different assumptions. We consider what happens if we use broader considerations sets, if we adjust for the fact that we only observe part of search activity and if we adjust for the fact that not all applications will be successful.

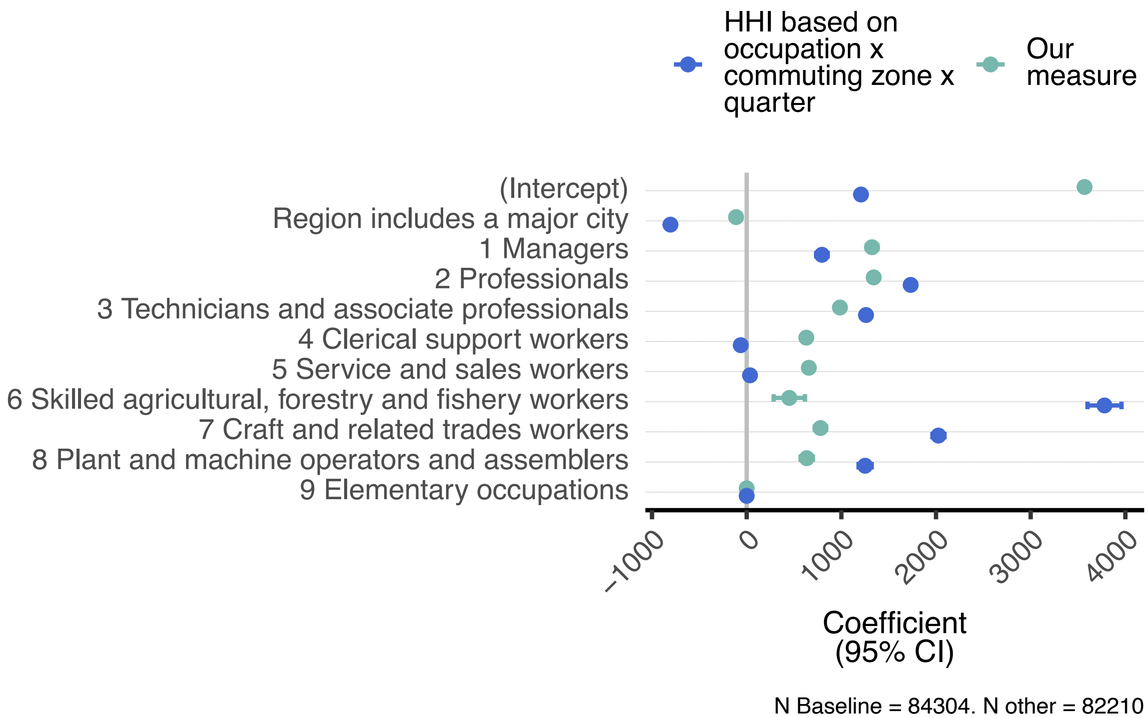

Figure 9: OLS regression of the HHI based on Equation 19 on vacancy characteristics. Major city = 5 biggest cities of Switzerland. Occupations are ISCO-08 definition, 1-digit level.

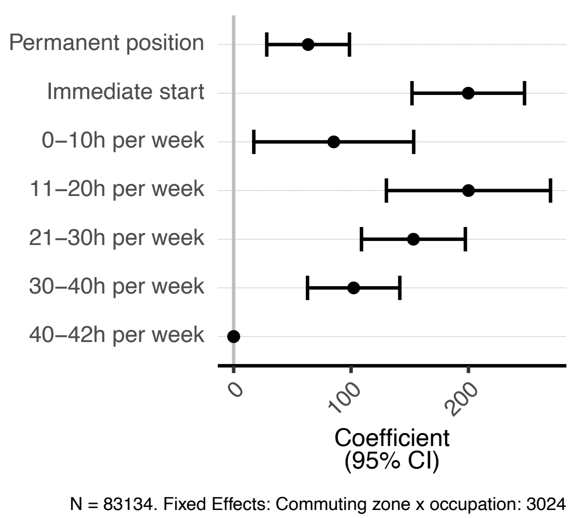

Figure 10: OLS regression of the HHI based on Equation 19 on vacancy characteristics conditional on the occupation (ISCO-08 4-digit) x commuting zone cell.

6.3.1 Broader Consideration Sets

If it takes time for applications to be resolved, the size of the consideration set in a single session will be too small as consideration sets in the past may still be 'in play' and future consideration set may be relevant to whether current jobs are taken. A too narrow definition of consideration sets will lead to an over-statement of labor market concentration.

We consider two broader measures of consideration sets. First, we go to the extreme and use as the consideration set all vacancies clicked on by the jobseeker whenever this occurred. Each jobseeker then has one, much larger, consideration set. This may go too far as jobs that were clicked on in the past may no longer be available (the median duration of a vacancy is 60 days). We have data on the time of the click on the vacancy and the date the vacancy was taken off the portal. So, as an alternative, for each vacancy a job seeker considers, we construct a consideration set that features all jobs that the jobseeker has already clicked on and which are still online and all jobs that the jobseeker will click on before the considered vacancy is taken off the portal. This measure can be seen as assuming that vacancies are open as long as they are on the platform and not longer available when they are removed from the platform.

6.3.2 Correcting the Estimate of λ

To construct the measure of competition based on treating sessions separately, it does not matter that we do not observe job search on other platforms as long as the sessions we observe are representative of all sessions. But, for the measures that group sessions it does matter. If the consideration set is all vacancies ever clicked on, unobserved search activity will lead to an under-statement of the size of the consideration set[10]. One can think of this problem as being that there are more sessions than those we observe i.e. λ, the frequency of sessions being under-estimated.

Suppose that the arrival rate of sessions on the platform is λ and the arrival rate of sessions on other platforms $\lambda_o(\lambda)$ which we allow to depend on λ as searchers may differ in the extent to which they use the job room. The overall arrival rate of sessions is then $[\lambda + \lambda_o(\lambda)]$. If we assume that sessions in the job room are equally effective as sessions elsewhere (a reasonable baseline assumption) the probability a job is obtained through the job room is given by $\rho = \frac{\lambda}{\lambda+\lambda_o(\lambda)}$. If we knew ρ we would want to use λ/ρ as the 'true' frequency of job sessions.

To obtain an estimate of ρ we use the fact that we observe the re-employment job and can see whether this is at a firm where we have observed a click. On average the probability that the firm

[10]The problem that only a sub-set of search is observed is common to many other studies e.g. those of applications

of the re-emplyoment job is among the clicked vacancies on the job room is 4.6% but there is a lot of variation across individuals. Figure 11 shows how the probability varies with activity on the job room.

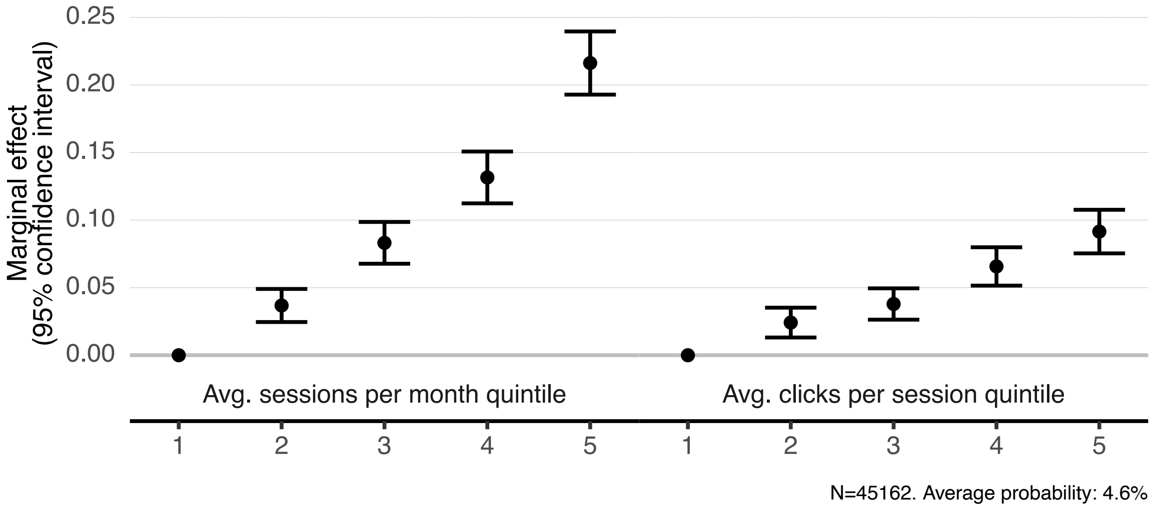

Figure 11: Marginal effects (at means) from a logistic regression. The outcome is a binary variable whether a jobseekers' new firm (after the unemployment spell) is among the firms in the clicked vacancy postings.

The baseline probability - for jobseekers in the bottom quintiles of the session rate and the number of clicks per session - is 0.9%; these are probably jobseekers who use the job room very little. Jobseekers with more activity in the job room are more likely to obtain a job they clicked on in the job room. The predicted probabilities is around 24.5% for the jobseekers in the highest quintiles of the session rate and the number of clicks per session. The strongest predictor is the frequency of job room sessions rather than the average number of clicks per session. For every individual in our sample, we predict this probability $\hat{\rho}$ and scale up their clicks by $\frac{1}{\hat{\rho}}$. Thus, for a person with a predicted probability of 24.5% we would scale up their number of clicks by 1/0.245=4.1 and for a person with a predicted probability of 4.6% the scaling factor is 21.7.

6.3.3 Correcting the Estimate of C

As is common in many models of monopsony, the framework developed above assumes that workers can freely choose every employer in their consideration set. In reality, we know that many job applications are rejected so the number of clicks represents an over-estimate of the number of jobs the searcher actually has to choose from [11].

A simple correction to allow for this is to weight clicks by their probability of being successful,

[11] The directed search literature - see Wright et al., 2021 - explicitly takes account of this

which will be related to the total number of clicks on the vacancy. Define $C_{ij} = 1$ if individual i clicks on vacancy j and p_{ij} to be the probability of success. From the perspective of firm f the jobseeker considering firm f have consideration sets consisting of f and a probability weighted sum of all other firms considered so that the size is given by:

$$C_{ik}^{a} = C_{ik} + \sum_{j \neq k} p_{ij} C_{ij} \tag{22}$$

The intutition is the following. If jobseekers interested in this firm are also interested in 10 others but have a 10% chance of being offered those jobs, effectively there is only 1 other job being considered. In this formulation clicks on the vacancy being considered are not down-weighted by the probability of success because what is relevant for them is the number of applicants who do not have a better offer it is up to them to decide who to accept.

The 'HHI' for vacancy f would then be given by:

$$HHI_f = \frac{\sum_i \left(\frac{1}{C_{if}^{a}}\right)^2}{\sum_i \left(\frac{1}{C_{if}^{a}}\right)} \tag{23}$$

where the sum is over all individuals who click on vacancy f. To implement this we estimate p_{ij} in the following way. The total number of clicks for vacancy j is $A_j = \sum_i C_{ij}$. If a vacancy with A_j clicks in total (something we observe) leads to $R(A_j)$ recruits then the probability of an individual click being successful is $R(A_j)/A_j$. In the case where all vacancies lead to one hire the probability of an individual applicant getting a job is $p_j = 1/A_j$. This probability can be computed using all observed clicks not just from our sample of the unemployed. One might want to make a further adjustment for the fact that some clicks on a vacancy will be from other platforms; we do not do that for the moment.

6.3.4 Adjust for usage of job-room.ch

In our measures, a jobseeker with very few clicks on the portal will heavily influence the vacancy-level HHI. This is because of the double role of 1/C, as i) the weight a jobseeker receives in the computation of the vacancy's average, and ii) as an indicator for the 'market share' of the vacancy in the jobseeker's choice (see eq. 17). However, one could argue that jobseekers with very few clicks are not 'seriously' searching for work on the job-room.

A further correction, therefore, weighs down jobseekers who have a low probability of finding employment from their search on the job-room. The weight is an estimate of the probability of finding employment from a click on the portal. In any given month, it is modeled as the probability of finding employment the next month, given the click history on job-room.ch, multiplied by the probability that the firm of the re-employment job is among the clicked vacancies on the job room, ρ from Section 6.3.2. This correction might be simplistic as it assumes that the usage of job-room is uncorrelated with the options available to the jobseeker. If jobseekers click on fewer jobs because there are fewer options available, this will make the correction underestimate the true extent of concentration.

The probability of finding a job within the next month, given the number of clicks, is obtained from a monthly hazard model. The outcome is the hazard of finding employment the next month, $t+1$, modeled using a complementary loglog specification, $1 - h(x\beta) = e^{-e^{x\beta}}$. The explaining variables are the lags of the number of clicks on job-room in $t-1, t-2, ..$

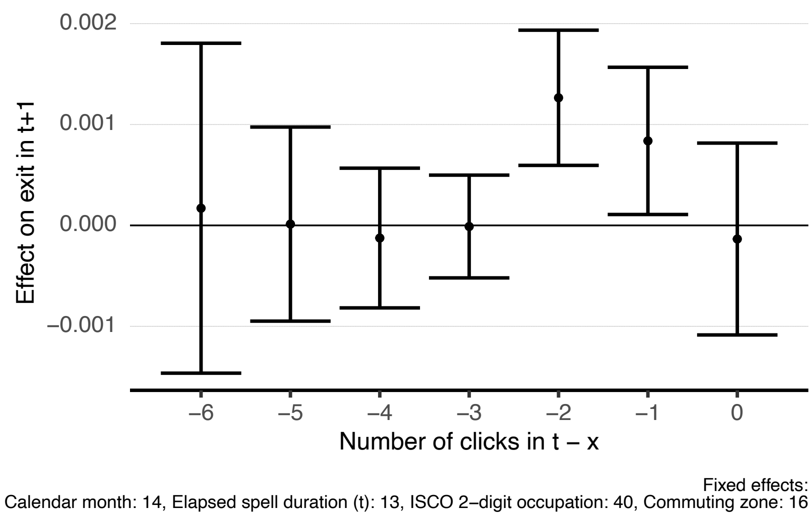

Figure 12: Coefficients from a monthly complementary log-log hazard model. The outcome is whether the jobseeker finds employment in the next month.

Figure 12 shows the result of the hazard model. We find that more clicks are associated with a higher unemployment probability and that only clicks two to three months ago have an effect. 10 clicks in month t lead to a 1.2% increase in the exit probability three months later.

6.4 Corrected Measures of Labor Market Concentration

As outlined in the previous subsections, our measure could be biased upwards or downwards. Table 3 presents the adjusted measures using different assumptions. It shows the average over all vacancies for a range of adjustments.

The level of concentration is affected by the assumptions made. As expected, broader definition

	(1)	(2)	(3)	(4)
Separate consideration sets by session	4195	4195	8700	8700
One consideration set by spell	1034	28	5074	569
All clicked and online vacancies in consideration set	1375	67	6156	859
Adjusted for other search channels (λ)		X		X
Adjusted for rejection (C)			X	X

Table 3: Mean vacancy-level HHI for different measures and corrections

of the consideration set, and adjusting for unobserved job search has the effect of reducing measured concentration, often by a large amount. But correcting for the probability of success moves things in the opposite direction, partially offsetting the influence of the previous corrections on the average.

To give some idea of the impact of different corrections, Figure 13 compares the unadjusted version of our measure, based on equation 19 to two other measures based on broader consideration sets and adjusted for unobserved search and the job finding probability.

The baseline measure has a mean of 4195 suggesting that jobseekers are only considering about 2.4 firms. When adjusting for a broader consideration set, when all clicks are included the mean is 1034 (equivalent to about 10 firms) and when looking at the set of clicked and online vacancies it is 1375 (equivalent to about 7 firms).

Figure 14 looks at the effect of down-weighting sessions of jobseekers not very actively using the job-room. The graph shows that this adjustment reduces the bi-modality of the HHI distribution. The mean concentration index after this adjustment is slightly lower than the unadjusted measure, at 3751, equal to 2.7 firms competing for a worker.

A limitation of our approach is that the levels of the measurement differ vastly depending on the assumptions made. While the levels of the measures differ, the patterns over vacancy characteristics remain largely consistent, as shown by Appendix Figure 20. The graph plots the coefficients of regressions of the index on vacancy characteristics as in Figure 9, but also adding the measures using the set of clicked and still online vacancies and applying the two adjustments.

A further concern is that the scaling using the actual jobs found is limited since a lot of factors affect the job found, and there is just one job found per spell, naturally limiting the number of observations. A future version of this study will leverage data on the universe of applications made by some of the jobseekers in our sample to refine the assumptions and corrections.[12]

[12]This data will be made available to us in the near future.

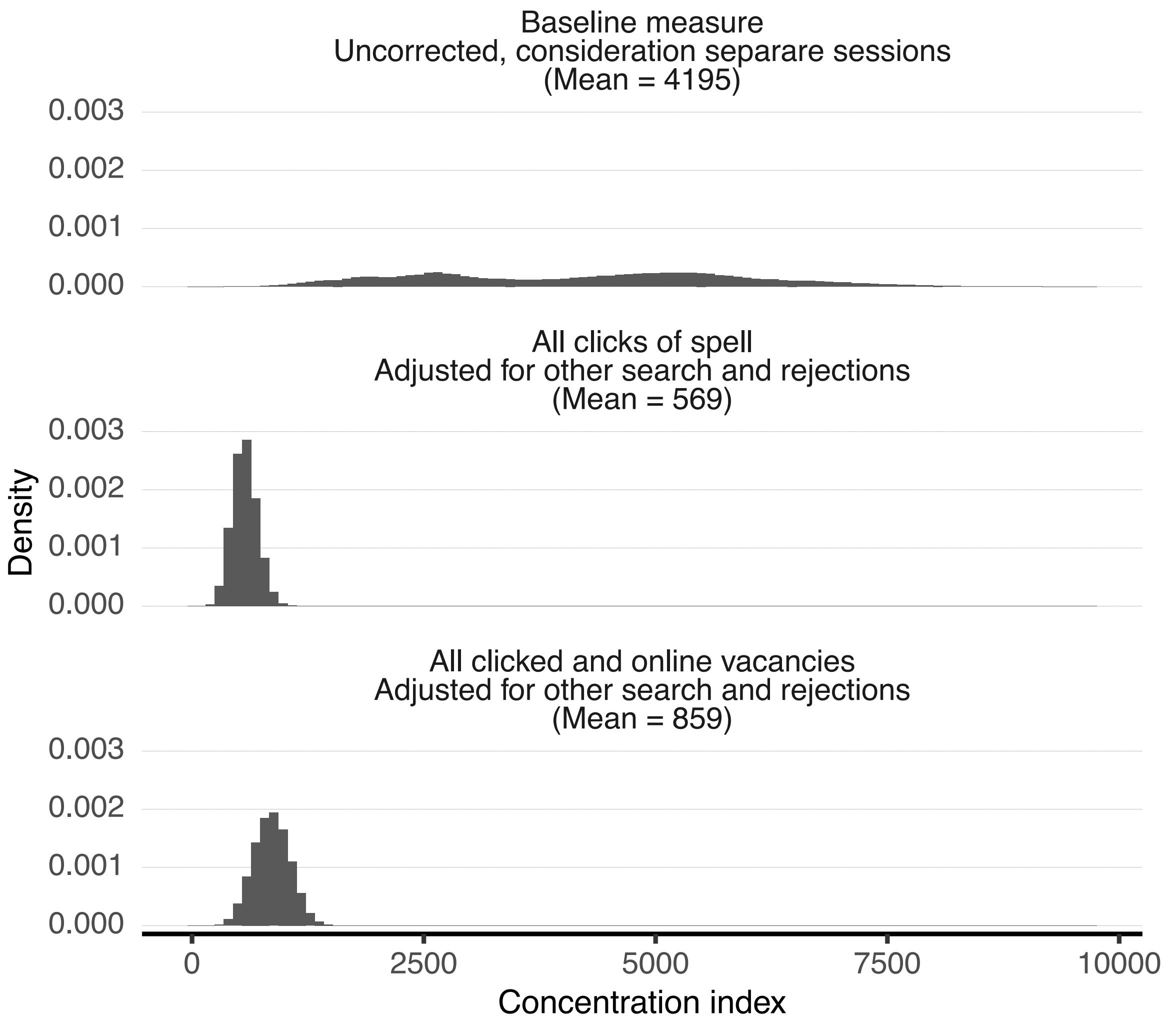

Figure 13: Distribution of the HHI with different corrections

6.5 Recurring vacancies and firms in the consideration set

12% of clicked vacancies are clicked by a jobseeker in more than one session. Our baseline measure assumes that these vacancies are fully considered again in the subsequent sessions and includes them as separate observations in the index computation. However, one might argue that this overestimates the choice a jobseeker has. Figure 15 compares the baseline measure to a version, where only the first click on a vacancy is counted towards the consideration sets, all subsequent clicks are ignored. The figure also shows a version of the HHI where each firm is only considered once and clicks on already-seen firms are not counted to the consideration set. These adjustments yield slightly higher estimates of employer market power. The correlation between the baseline and the adjusted measures is 0.84 and 0.62, respectively.

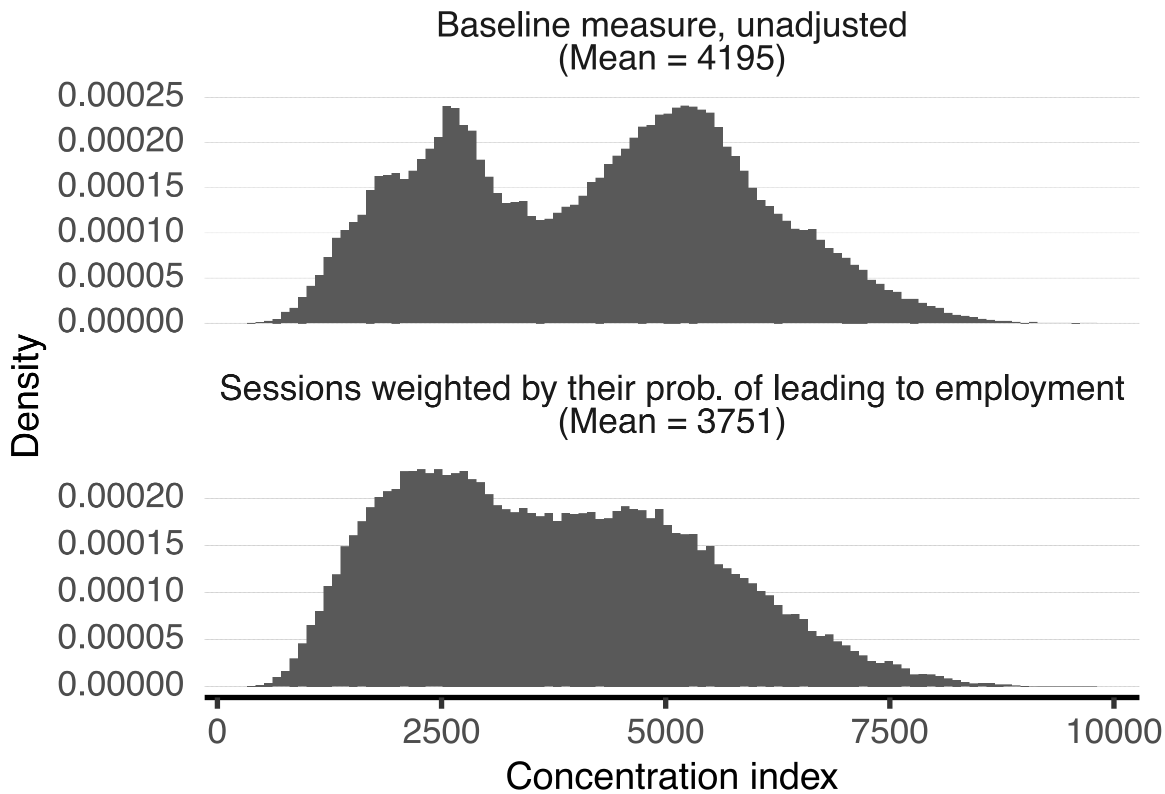

Figure 14: Distribution of the HHI with a downweighting for sessions by jobseekers not very actively using the job portal.

6.6 Varying Click 'Quality'

So far we have assumed that all clicks were equally effective in sustaining labor market competition; implicitly the formulae used were based on the assumption of a symmetric equilibrium in which all firms were identical. In reality, not all firms are equally attractive to workers and this section investigates whether taking account of that matters for the measures of market power.

Continue to maintain the assumption that unemployment is always unattractive but now allow for job vacancies to differ in their attractiveness to workers. In this case (15) can be written as:

$$\theta_i\left(w_f;\mathcal{F}\right)=\frac{e^{\beta w_f}}{\sum_{j\epsilon\mathcal{F}_i}e^{\beta w_j}} \tag{24}$$

This can then be aggregated to the vacancy level using (19) to give

$$\varepsilon_f=\beta\frac{\sum_i\theta_i\left(w_f;\mathcal{F}\right)\left[1-\theta_i\left(w_f;\mathcal{F}\right)\right]}{\sum_i\theta_i\left(w_f;\mathcal{F}\right)}=\beta\left[1-\frac{\sum_i\theta_i\left(w_f;\mathcal{F}\right)^2}{\sum_i\theta_i\left(w_f;\mathcal{F}\right)}\right] \tag{25}$$

This has similarities to earlier formula but now jobs that workers are more interested in attract

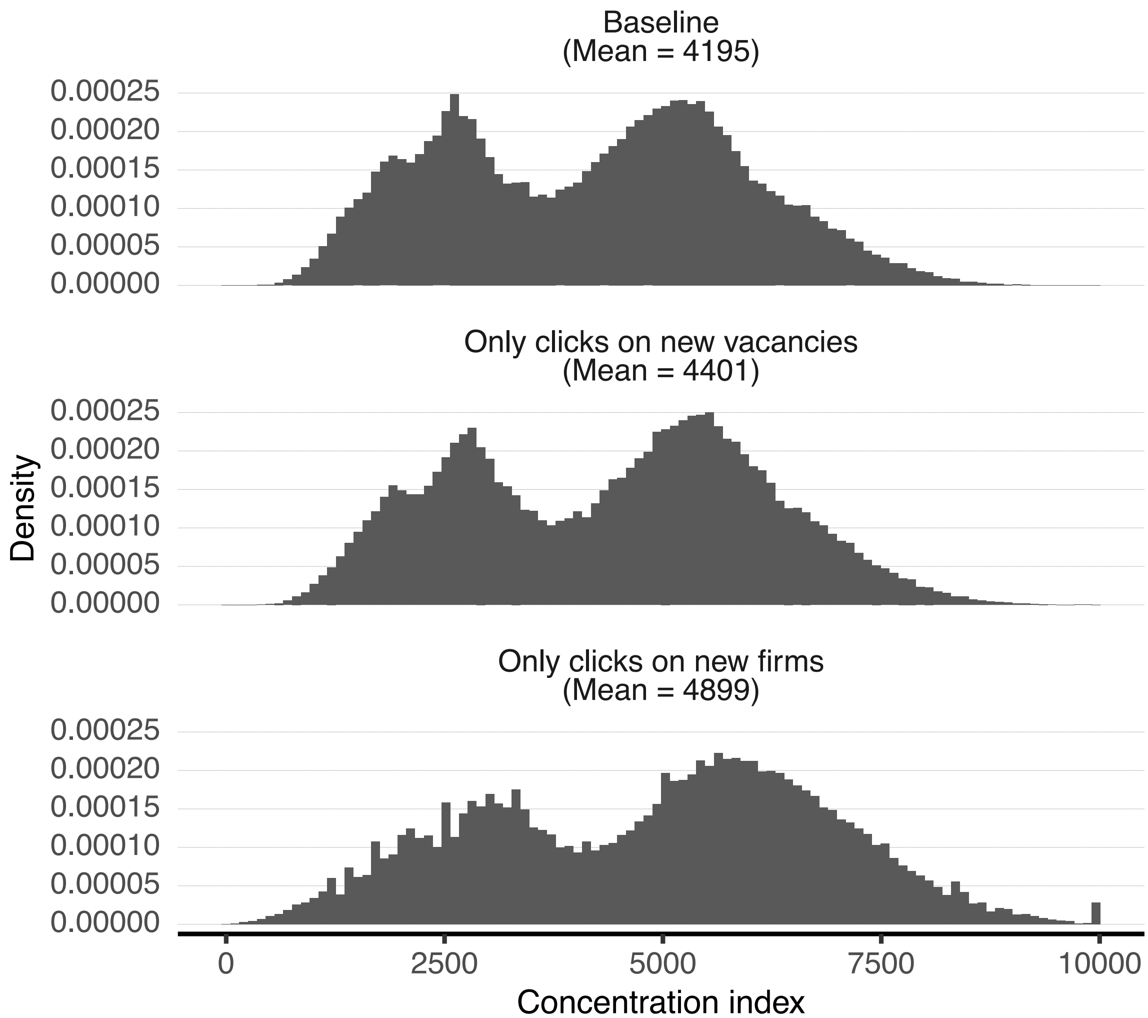

Figure 15: Distribution of the HHI with different treatment of re-occurring vacancies and firms.

a greater weight i.e. they loom larger in the worker's consideration set though they may not necessarily be larger employers. To implement this we use the following method. We take the sample of 5173 jobseekers who end up in employment at a firm we observe they have clicked on. We then estimate a multinomial logit model for the successful click relative to the others. The explanatory variables are the geographical distance to the job, the occupational distance to the job (Klaeui et al., 2024) as well as whether the hours worked correspond to the jobseeker's stated preference in hours worked[13]. We allow for a flexible functional form for the continuous variables.

The estimates imply that a better match in location, occupation and hours worked increases the probability of taking up employment at a particular job. To give a flavour of the model imagine a hypothetical consideration set of 5 firms where 4 jobs have the median match in occupation,

[13]In the first meeting with a caseworker, at the start of the unemployment spell, a jobseeker's desired hours worked per week are recorded among other information.

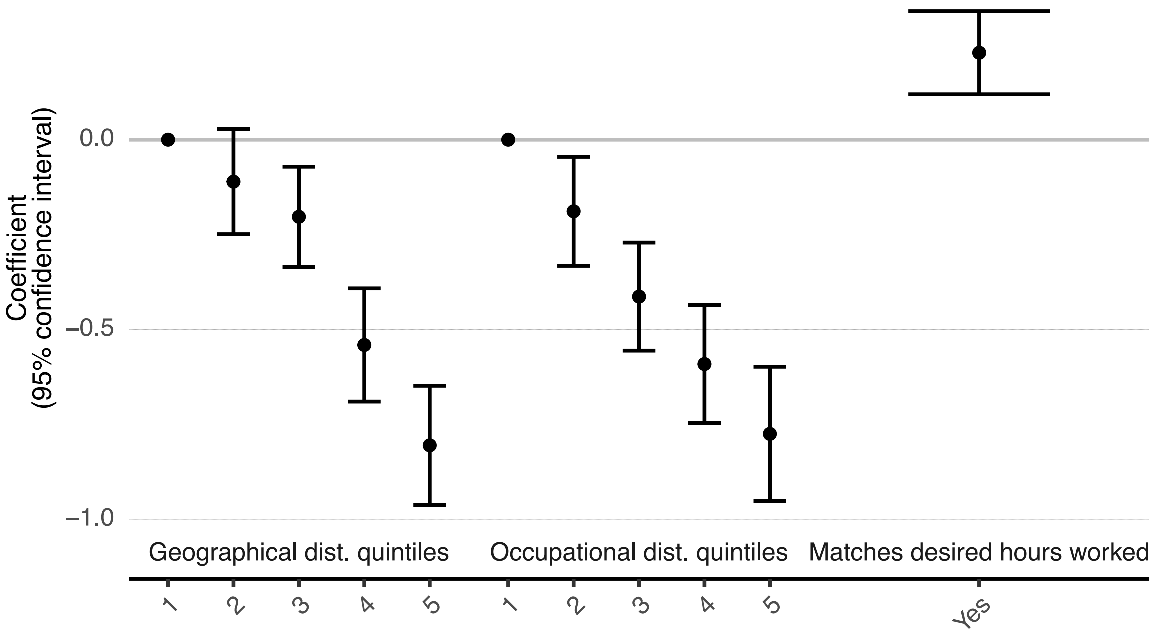

Figure 16: Coefficients from an multinomial logit regression. The dependent variable is whether the jobseeker finds a job at a firm or not and the choice set are all clicked vacancy postings. The sample consists of the 5106 jobseekers who find a job at one of the clicked firms and don't have missing information on the distance to the job found. If multiple vacancy postings in a choice set belong to the firm where a jobseeker finds a job, the dependent variable is set to 1 for all those jobs.

location and desired hours but one job is in the first distance quintile. The closer job would have a match probability of 23% and the other 4 jobs a probability of 19% each. The same exercise for occupational distance and desired working hours leads a very similar pattern of market shares.

We will refer to the predicted value of the utility of a vacancy to an individual as job quality.

We then use these estimates to compute (24) and this can then be used in the formula (19) to provide an alternative measure of employer market power over unemployed workers. Figure 17 compares the distribution of the index allowing for vacancy heterogeneity with our baseline index. Both are computed regarding each session as a separate consideration set.

The results show that allowing for vacancy heterogeneity has little impact on the concentration measure. The average concentration is almost the same as for the baseline measure and the correlation coefficient between the two measures is 0.99. The similarity between the two versions also holds for the indices computed with different consideration set definition. These results suggest that the quantity of jobs considered by a jobseeker is the main driver of market power and that variation in quality relatively unimportant.

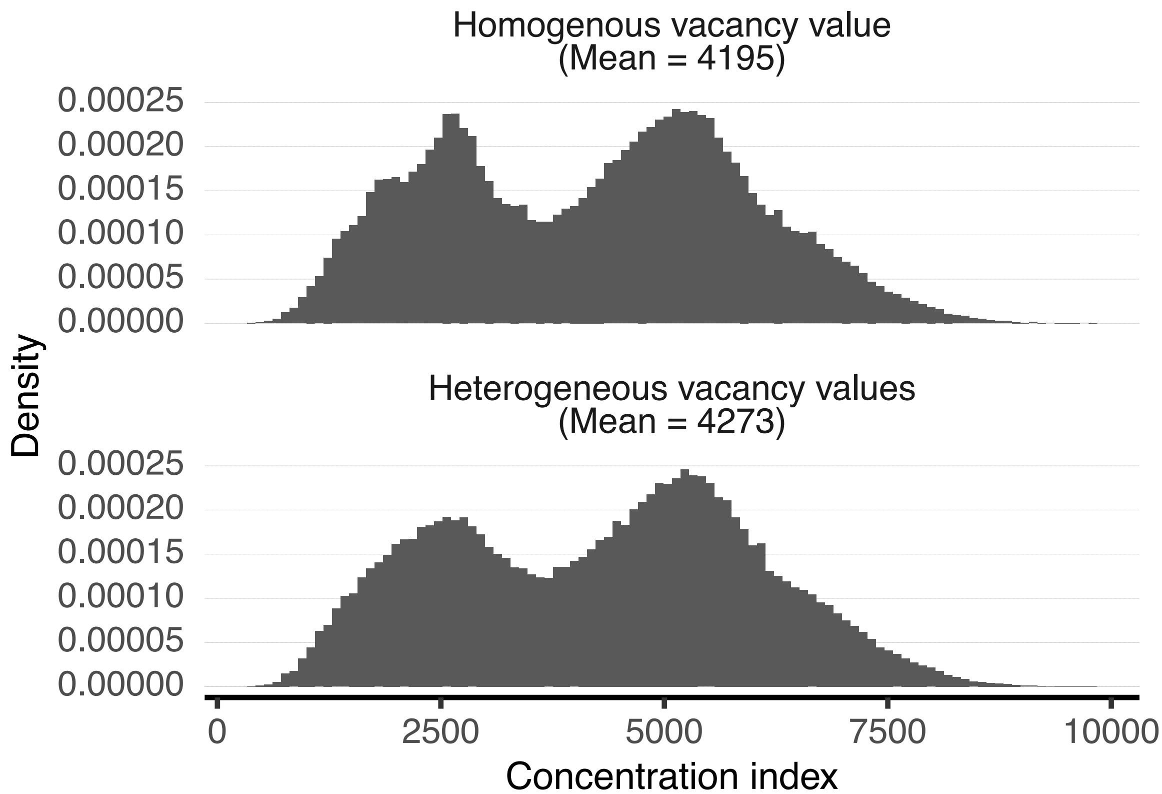

Figure 17: Distribution of the HHI based on Equation 19 over vacancy postings. To compute the HHI, each session is regarded as a separate consideration set.

7 Job Search to Sustain Labor Market Competition; Too Little or Too Narrow?

Jobseekers have an incentive to search to find more attractive work faster. But, if wage determination is not individualized, individuals do not have a strong incentive to search to make labor markets more competitive as most of the benefits would flow to others (though there would also be costs for employers). In recent years there have been a number of evaluations of policies designed to increase the job search of the unemployed and make it broader (e.g Belot et al., 2019; Klaauw and Vethaak, 2022; Dhia et al., 2022). These report mixed outcomes.

Increasing the quantity of job search is likely to increase competition on labor markets. But increasing the breadth of job search may not have positive effects if it means workers considering more jobs in which they have little interest or low prospects of getting them. In terms of the framework laid out above, competition is maximized for a given number of clicks if those clicks have the same probability of resulting in a job. A key question is whether it is feasible for jobseekers to increase the quantity of job search without sacrificing quality.

To shed some light on this we use the estimated coefficients from the model of the previous section to compute the predicted job quality for all individuals in all vacancies, whether or not they have been clicked. There is strong evidence that the jobs that are clicked on are directed towards those with higher job quality. We compare the actual distribution of job quality in clicks with what would be found using the same number of clicks but choosing the vacancies at random[14]. Comparing Figure 18 (1) and (2) shows that this does much worse than the observed clicks implying that job search is directed towards jobs the searcher finds more appealing; this is not surprising.[15]

But could search be better-directed? To answer this question, we take random sets of vacancies of a certain size and choose the 'best' set of jobs equal to the actual number of clicks, this is shown in specification (3) in Figure 18. What is perhaps surprising is that there does not seem to be much gain from doing this. This is even more striking when one considers that the jobs that are clicked are likely to have some component of utility observable to the searcher but not the researcher.

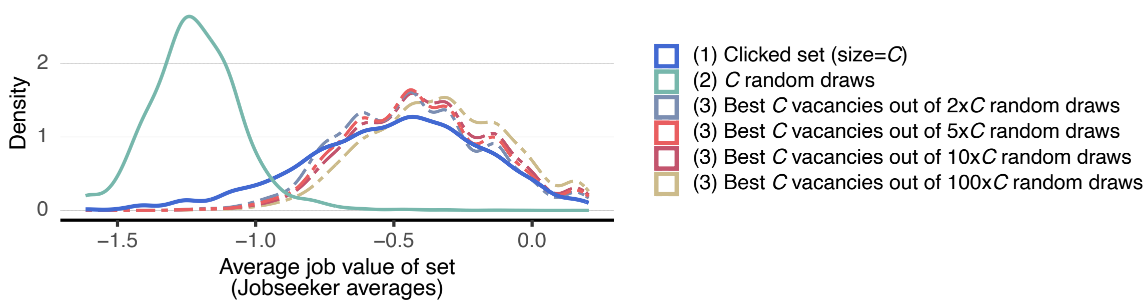

Figure 18: Average job value of different sets of vacancies. Averages by jobseeker. The value is computed analogous to the inclusive value from a logit model, $\bar{v_i} = log(1/N * \sum_j exp(v_{ij}))$, using the estimates from Section 6.6.

The direction of search does not seem sub-optimal. But can the quantity of job search be increased without any clear loss in quality? I.e. are the unemployed not clicking on all the available jobs that we think they might be interested in? Figure 19 shows the same exercise as above but increases the number of jobs in the sets. The results suggest that increasing the number of jobs in the set does not lead to a loss in quality. The average values from sets that are 1.5 times or twice as big as the actually clicked set are not lower than the average value from the clicked set, they are actually slightly higher. This holds true even though our 'best sets' are not chosen from the entire population but only from a random sample of 100 other jobs per clicked job[16]. However, when we push the exercise and increase the size of the set by larger factors, such as 5 or 10, the

[14]We sample the random vacancies from the distribution of vacancies with at least one click and we sample at the jobseeker-month level. This ensures that the vacancies were available to the jobseeker at the time of their search.

[15]Analogous to the computation of the inclusive value in a nested logit model, the average value is computed the following way $\bar{v_i} = log(1/N * \sum_j exp(v_{ij}))$

[16]This is due to computational constraints.

average quality starts to deteriorate. This suggests that job search activity can likely be increased without a clear loss in quality, but increasing it too much can have negative effects. Interventions with the aim to increase the quantity of jobseekers search may, hence, be beneficial in terms of reducing labor market competition, even creating externalities on other jobseekers[17]. However, this is only the case if the job-search advice, such as occupations or locations to target, is able to keep the quality of the jobs added to the consideration sets constant. Our back-of-the-envelope results suggest that this is possible for moderate interventions but might be more difficult for more disruptive interventions.

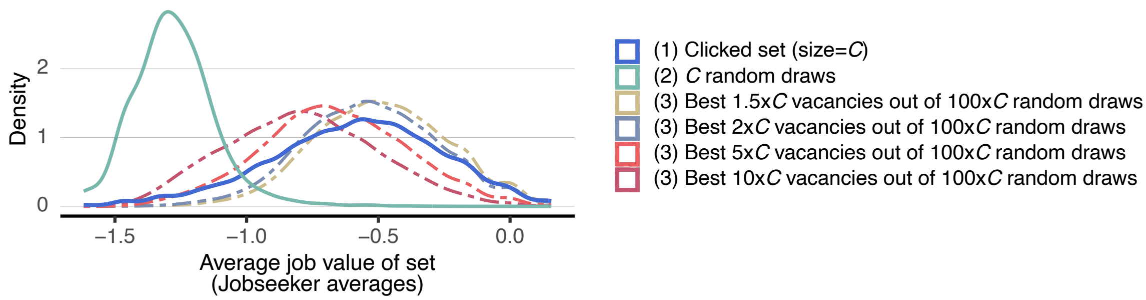

Figure 19: Average job value of sets of vacancies. The sets of vacancies which jobseekers click on, (1), are compared to counterfactual sets. (2) shows a set of randomly chosen jobs with the same size, C, as the clicked set. (3) samples 100 times C vacancies and chooses the X best of them, it compares different sizes of sets: $1.5C$, $2C$,$5C$ and $10C$. The graph reports the distribution of average values of the sets over jobseekers. The value of a set is computed analogous to the inclusive value from a logit model, $\bar{v}_i = log(1/N * \sum_j exp(v_{ij}))$, using the estimates from Section 6.6

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8 Conclusion

We have argued that job search is likely to be important in sustaining competition in labor markets. The larger the set of firms being considered by jobseekers, the more competitive the market is likely to be. Most theoretical models of employer market power make assumptions about the consideration sets of jobseekers, either that they are the universe of firms in a labor market (in the new classical models) or that opportunities arrive one at a time (in the modern monopsony models based on frictions). This paper has tried to assess how large consideration sets actually are. We present a framework to develop indices of labor market concentration akin to, but different from, the commonly used HHI indices. We then compute these indices using data on Swiss UI recipients search activity on a platform, using clicks on vacancies to define their consideration sets.

[17]When firms can not wage-discriminate on the individual level, an increase in the average C per jobseeker leads to lower employer market power, even for the jobseekers that don't increase their own search.

We discuss how these indices are affected by different assumptions that could be made about the search process.

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Appendix A

8.1 Proof of Proposition 1

8.1.1 Proof of Proposition 1.1

Both $H()$ and $G_u()$ are increasing in w_f so (4) shows $n(w_f;\mathcal{F})$ is.

8.1.2 Proof of Proposition 1.2

$H()$ and $G_u()$ are log-concave implies $H()G_u()$ is log-concave. And $n(w_f;\mathcal{F})$ is then a linear combination of log-concave functions which is known to also be log-concave. Log-concavity of $n(w_f;\mathcal{F})$ implies that the elasticity of $n(w_f;\mathcal{F})$ with respect to w_f $\frac{\partial log n(w_f;\mathcal{F})}{\partial w_f}$ is a decreasing function of w_f.

8.1.3 Proof of Proposition 1.3

Suppose we have a set $\mathcal{F}$ and add an extra firm j to it. Using (4) and (2) Labor supply to the firm can now be written as:

$$n(w_f;\mathcal{F}\cup\{j\}) = \int_{\eta_{min}}^{\eta_{max}} g(\eta)\, H(\beta w_f+\eta;\mathcal{F}\backslash\{f\})\, G(\beta(w_f-w_j)+\eta)\, G_u(\beta(w_f-b)+\eta)\, d\eta \tag{26}$$

To minimize notation define $Z(\beta w_f+\eta) = H(\beta w_f+\eta;\mathcal{F}\backslash\{f\})\, G_u(\beta(w_f-b)+\eta)$. $Z(\beta w_f+\eta)$ will be an increasing log-concave function. Then (26) can be written as:

$$n(w_f;\mathcal{F}\cup\{j\}) = \int_{\eta_{min}}^{\eta_{max}} g(\eta)\, Z(\beta w_f+\eta)\, G(\beta(w_f-w_j)+\eta)\, d\eta \tag{27}$$

Define a variable y as:

$$y(\eta, w_f) = \frac{\int_{\eta_{min}}^{\eta} g(x)\, Z(\beta w_f+x)\, dx}{\int_{\eta_{min}}^{\eta_{max}} g(x)\, Z(\beta w_f+x)\, dx} = \frac{\int_{\eta_{min}}^{\eta} g(x)\, Z(\beta w_f+x)\, dx}{n(w_f;\mathcal{F})} \tag{28}$$

For future use denote the inverse of this function as $\eta(y, w_f)$. Differentiating (28) we have that:

$$n(w_f;\mathcal{F})\, dy = g(\eta)\, Z(\beta w_f+\eta)\, d\eta \tag{29}$$

Using (29) to changing the variable of integration in (27) from η to y we have that:

$$n(w_f;\mathcal{F}\cup\{j\}) = n(w_f;\mathcal{F}) \int_0^1 G[\beta(w_f-w_j)+\eta(y, w_f)]\, dy \tag{30}$$

Differentiating (30) with respect to $w_f$we have that:

$$\frac{\partial logn\left(w_f;\mathcal{F}\cup\{j\}\right)}{\partial w_f}=\frac{\partial logn\left(w_f;\mathcal{F}\right)}{\partial w_f}+\frac{\int_0^1 G'\left(\right)\left[\beta+\frac{\partial\eta(y,w_f)}{\partial w_f}\right]dy}{\int_0^1 G\left[\beta\left(w_f-w_j\right)+\eta\left(y,w_f\right)\right]dy} \tag{31}$$

Inspection of (31) shows the labor supply elasticity will be higher with the extra firm if the final term is positive for which a sufficient condition is that:

$$\left[\beta+\frac{\partial\eta\left(y,w_f\right)}{\partial w_f}\right]>0 \tag{32}$$

for all y. Taking logs of (28) and differentiating we have that:

$$0=\frac{\int_{\eta_{min}}^{\eta} g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta} g\left(x\right)Z\left(\beta w_f+x\right)dx}-\frac{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z\left(\beta w_f+x\right)dx}+\frac{g\left(\eta\right)Z\left(\beta w_f+\eta\right)}{\int_{\eta_{min}}^{\eta} g\left(x\right)Z\left(\beta w_f+x\right)dx}\frac{\partial\eta\left(y,w_f\right)}{\partial w_f} \tag{33}$$

The condition (32) can then be written as:

$$g\left(\eta\right)Z\left(\beta w_f+\eta\right)-\int_{\eta_{min}}^{\eta} g\left(x\right)Z'\left(\beta w_f+x\right)dx+\int_{\eta_{min}}^{\eta} g\left(x\right)Z\left(\beta w_f+x\right)dx\frac{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{34}$$

Integrating the second term by parts this condition can be written as:

$$\int_{\eta_{min}}^{\eta} g'\left(x\right)Z\left(\beta w_f+x\right)dx+\int_{\eta_{min}}^{\eta} g\left(x\right)Z\left(\beta w_f+x\right)dx\frac{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{35}$$

Integrating the numerator of the final term by parts and dividing by the first part of the final term, this can be written as:

$$\frac{\int_{\eta_{min}}^{\eta}\frac{g'(x)}{g(x)}g\left(x\right)Z\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta} g\left(x\right)Z\left(\beta w_f+x\right)dx}-\frac{\int_{\eta_{min}}^{\eta_{max}}\frac{g'(x)}{g(x)}g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z\left(\beta w_f+x\right)dx}+\frac{g\left(\eta_{max}\right)Z'\left(\beta w_f+\eta_{max}\right)}{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{36}$$

This can be written as:

$$E\left[\frac{g'\left(x\right)}{g\left(x\right)}|x\leq\eta\right]-E\left[\frac{g'\left(x\right)}{g\left(x\right)}|x\leq\eta_{max}\right]+\frac{g\left(\eta_{max}\right)Z'\left(\beta w_f+\eta_{max}\right)}{\int_{\eta_{min}}^{\eta_{max}} g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{37}$$

From log concavity of g, $\frac{g'(x)}{g(x)}$ is decreasing in x so that the first term is bigger than the second term. As the final term is also positive this proves the Proposition.

8.2 Proof of Proposition 2

8.2.1 Proof of Proposition 2.1

Consider the case where there are C firms all but one paying the same wage w and employment is always preferred to unemployment. We will consider a single firm that possibly deviates by pying a wage w_f (though it won't in equilibrium). Labor supply 14 then becomes:

$$n(w_f; C) = \int_{\eta_{min}}^{\eta_{max}} g(\eta) G(\beta(w_f - w) + \eta)^{C-1} d\eta \tag{38}$$

and the elasticity of labor supply can be written as:

$$\epsilon = (C-1) \frac{\int_{\eta_{min}}^{\eta_{max}} g(\eta) g(\beta(w_f - w) + \eta) G(\beta(w_f - w) + \eta)^{C-2} d\eta}{\int_{\eta_{min}}^{\eta_{max}} g(\eta) G(\beta(w_f - w) + \eta)^{C-1} d\eta} \tag{39}$$

Evaluating at a symmetric equilibrium $w_f = w$ we have that:

$$\epsilon = C(C-1) \int_{\eta_{min}}^{\eta_{max}} g(\eta)^2 G(\eta)^{C-2} d\eta \tag{40}$$

as the numerator of (39) will be $1/C$. Integrating by parts we have that:

$$\epsilon = C \left[g(\eta) G(\eta)^{C-1} \right]_{\eta_{min}}^{\eta_{max}} - C \int_{\eta_{min}}^{\eta_{max}} g'(\eta) G(\eta)^{C-1} d\eta = Cg(\eta_{max}) - C \int_{\eta_{min}}^{\eta_{max}} \frac{g'(\eta)}{g(\eta)} g(\eta) G(\eta)^{C-1} d\eta \tag{41}$$

and integrating the final term by parts leads to:

$$\epsilon = Cg(\eta_{max}) - \left[\frac{g'(\eta)}{g(\eta)} G(\eta)^C \right]_{\eta_{min}}^{\eta_{max}} + \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)} \right]' G(\eta)^C d\eta \tag{42}$$

which becomes (5).

8.2.2 Proof of Proposition 2.2

Differentiating (5) with respect to C leads to:

$$\frac{\partial \epsilon}{\partial C} = g(\eta_{max}) + \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)} \right]' [logG(\eta)] G(\eta)^C d\eta \tag{43}$$

The first term is obviously non-negative positive. The second term is also positive because log concavity of $g(\eta)$ implies that $\left[\frac{g'(\eta)}{g(\eta)}\right]' \leq 0$ and $logG(\eta) \leq 0$. Now differentiate again to give:

$$\frac{\partial^2 \epsilon}{\partial C^2} = \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)} \right]' [logG(\eta)]^2 G(\eta)^C d\eta \tag{44}$$

This must be non-positive proving concavity.

8.2.3 Proof of Proposition 2.3

Because $G(\eta) \leq 1$ the final two terms in (5) must be less than or equal to $\left[\frac{g'(\eta_{min})}{g(\eta_{min})}\right]$ for all C. So the limit of these terms must be finite. The limit of the elasticity is then finite if $g(\eta_{max}) = 0$, infinite if $g(\eta_{max}) > 0$.

8.3 Proof of Proposition 3

8.3.1 Proof of Proposition 3.1

An increase in $\frac{\lambda}{\delta}$leads to a shift in the distribution of x in the sense of first-order stochastic dominance. This causes weighted average to shift towards the case where more opportunities which by Proposition 1.3 leads to lower market power

8.3.2 Proof of Proposition 3.2

An increase in C leads to an increase in the number of opportunities for a given x in the sense of first-order stochastic dominance. By Proposition 1.3 this leads to lower market power for every x

8.4 The distribution of x

The rate at which workers move from having had 0 opportunities to having 1 offer is λ so total outflows from the state are $\lambda\phi(0)$; the inflows into this state are $\delta(1-\phi(0))$. Equating inflows and outflows gives us:

$$\phi(0) = \frac{\delta}{\delta+\lambda} \tag{45}$$

The rate at which workers move from having had $x-1$ opportunities to having x offers is λ. The rate at which workers exit having had x opportunities is δ to unemployment and λ to having $(x+1)$. Hence the fraction of workers having had x opportunities, $\phi(x)$ follows the recursion:

$$\phi(x) = \frac{\lambda}{\delta+\lambda}\phi(x-1) \tag{46}$$

Combining (45) and (46) leads to (6)

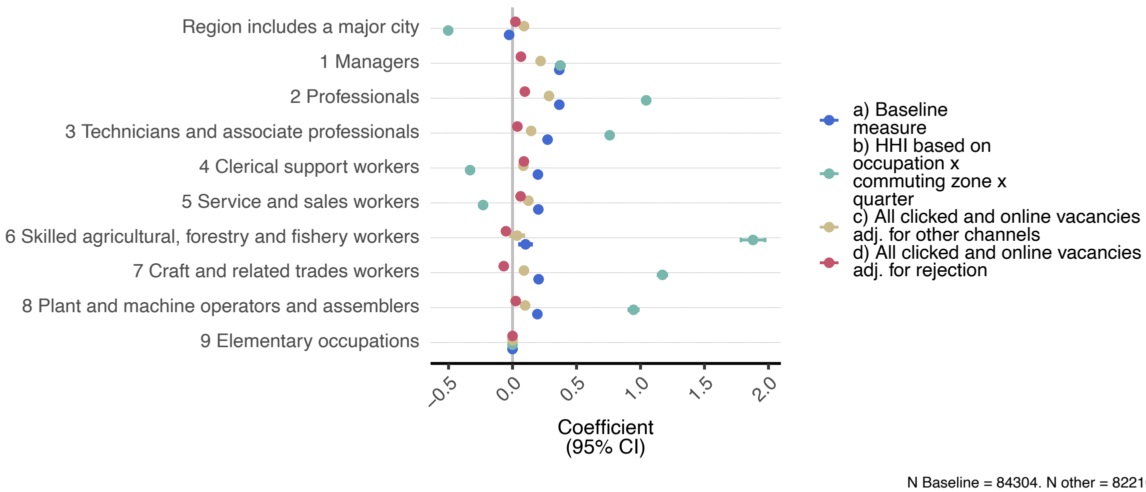

Figure 20: OLS regression of the log(HHI) based on Equation 19 on vacancy characteristics. Major city = 5 biggest cities of Switzerland. Occupations are ISCO-08 definition, 1-digit level.

Appendix B

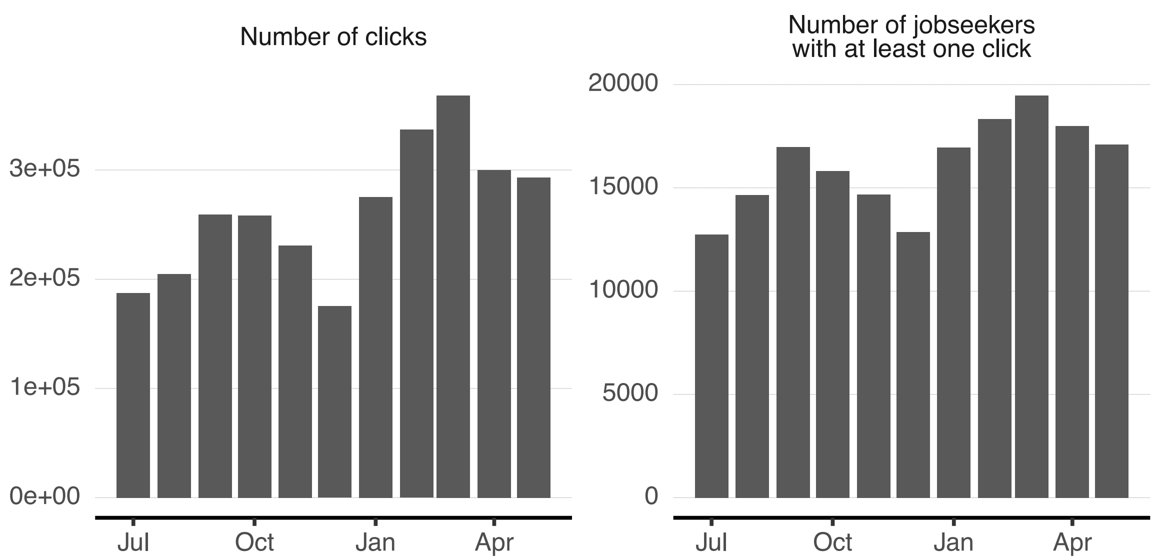

Figure 21: Usage of the job room over time by the registered jobseekers in our sample.

Measurement	Mean	SD	Min	p25	p50	p75	Max
c	15.83	49.84	1.00	4.00	8.00	15.00	1647.00
c corrected	1.41	2.39	1.00	1.03	1.09	1.25	81.82
total clicks	243.74	373.30	1.00	57.00	132.00	277.00	4524.00
total c lambda corrected	1234.17	1528.14	56.59	463.77	782.79	1406.58	18444.48
total clicks c corrected	6.62	15.08	1.00	1.83	3.12	6.11	281.91
total clicks both corrected	36.22	62.47	4.82	15.52	22.35	35.46	1149.35
n overlap	98.48	177.04	1.00	25.00	53.00	108.00	3761.00
overlap lambda cor	516.98	747.75	4.08	204.86	331.42	559.96	15333.71
overlap c corrected	3.63	8.67	0.96	1.35	1.89	3.18	237.94
overlap both cor	21.85	37.51	4.07	10.02	14.14	21.66	970.09
c new firms	8.42	13.89	1.00	3.00	5.00	10.00	373.00
c new ads	14.75	47.59	1.00	4.00	7.00	14.00	1463.00

Table 4: The input quantities for the different HHI measures. Summary statistics over jobseeker-ad pairs.

Measurement	Mean	SD	Min	p25	p50	p75	Max
share by session	0.21	0.24	0	0.06	0.13	0.25	1
share by spell	0.02	0.06	0	0.00	0.01	0.02	1

Table 5: The input quantities for the HHI measures taking into account vacancy heterogeneity. Summary statistics over jobseeker-ad pairs.

Appendix C: How Search Activity Varies Over a Spell of Unemployment

While Figures 5 and 6 show the number of sessions and clicks per session on average, there may be considerable heterogeneity. Figures 26 and 27 present some simple regressions on how the number of sessions and the number of clicks per session vary. We are particularly interested in how search intensity varies over the duration of the unemployment spell. The first specification shows how the two dimensions of search activity vary with duration when only controls for time-effects are included (by adding dummies for the four quarters for which we have data to the regression[18]). The duration dependence can be the result of true duration dependence or unobserved heterogeneity if (as is the case) those with greater search intensity have shorter durations. The second specification shows how results change when we control for the individual characteristics of the unemployed and the final specification when we control for individual fixed effects.

Figure 26 shows that, on average, a jobseeker has 2.13 sessions in the first month of spell and this number declines by around 10% in the second month and goes down to a constant level 40%

[18] The four quarters are 2020Q3, 2020Q4, 2021Q1, 2022Q2.

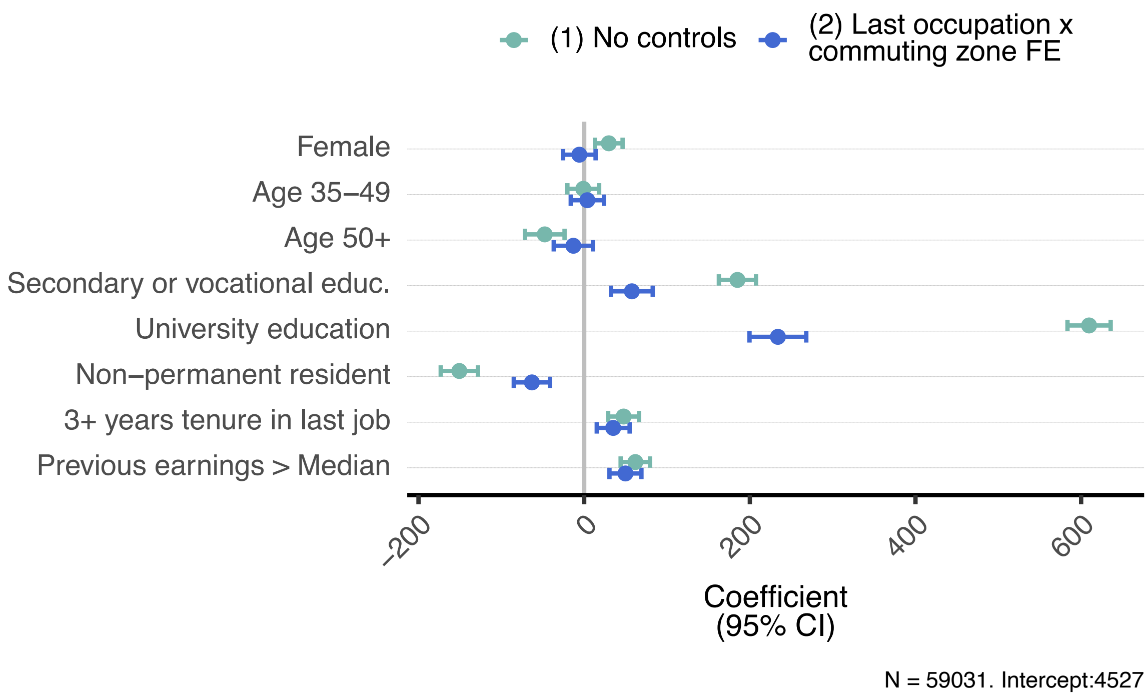

Figure 22: OLS regression of the jobseeker-level HHI on jobseeker characteristics. The jobseeker average HHI is computed as follows: $HHI_i = \sum_{f \in \mathcal{F}} \frac{s_{if}}{\sum s_{if}} HHI_f$. s_{ij} is the share of vacancy f in jobseekers i's portfolio, over the whole spell, where every session gets equal weights, e.g. if a jobseeker has 5 sessions and vacancy f gets clicked in one of the sessions together with 9 other vacancies, then $s_{if} = 1/50$. HHI_f is defined following equation 19, $HHI_f = \frac{\sum_i \left(\frac{1}{C_i}\right)^2}{\sum_i \left(\frac{1}{C_i}\right)}$

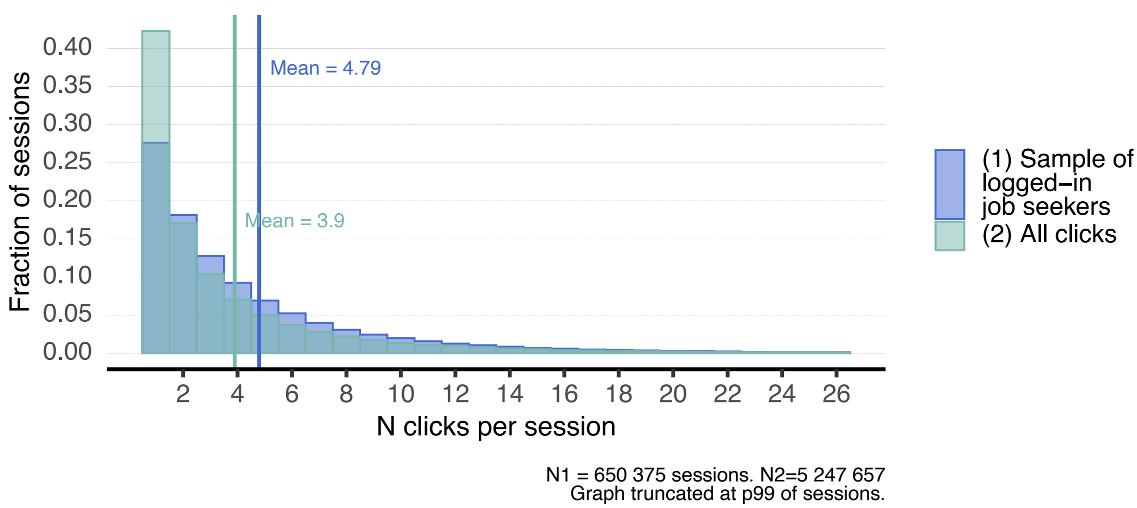

Figure 23: Distribution of number of clicks per session. Comparison between our sample of registered (and logged-in) jobseekers and all users of the platform. For the non logged-in users we define a search session by day (as in the other parts of the paper) and IP address. We exclude the IP addresses with a number of clicks higher than the 99.9 percentile (929 clicks)

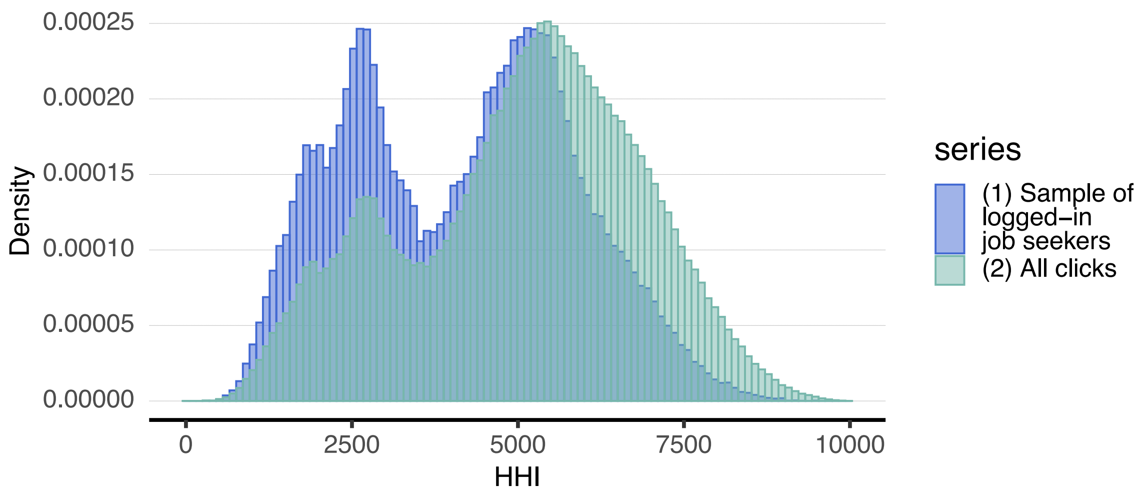

Figure 24: Distribution of the HHI calculated using the number of clicks per session as in Figure 7. Comparison between the HHI computed in our sample of registered (and logged-in) jobseekers and all users of the platform. For the non logged-in users we define a search session by day (as in the other parts of the paper) and IP address. We exclude the IP addresses with a number of clicks higher than the 99.9 percentile (929 clicks)

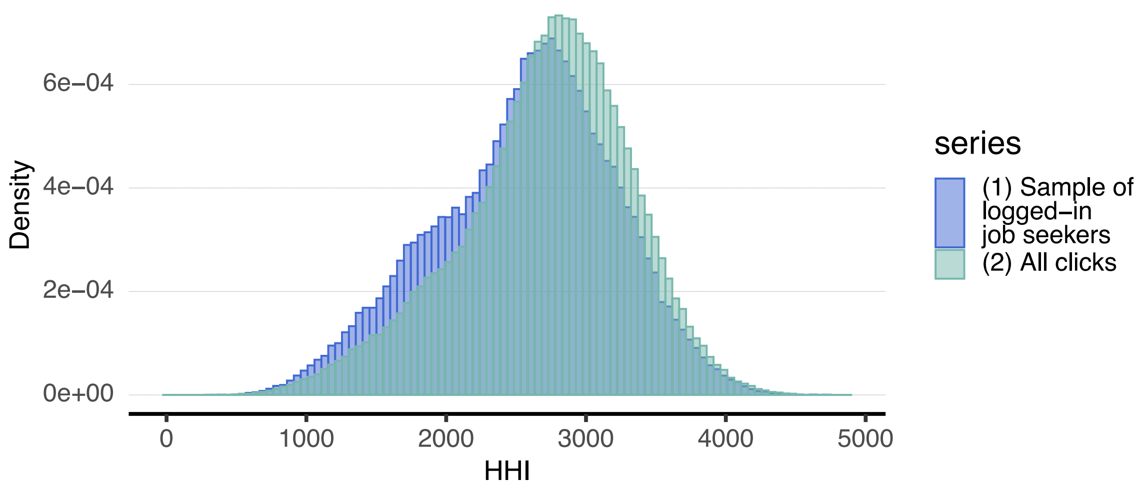

Figure 25: Distribution of the HHI calculated using the number of clicks per session as in Figure 7. This figure excludes sessions with 1 click only. Comparison between the HHI computed in our sample of registered (and logged-in) jobseekers and all users of the platform. For the non logged-in users we define a search session by day (as in the other parts of the paper) and IP address. We exclude the IP addresses with a number of clicks higher than the 99.9 percentile (929 clicks)

below the initial level after around 8 months. This pattern also holds conditional on last occupation, commuting zone, age, education, residence permit, insured earnings and tenure at the last job prior to unemployment. Once we control for unobserved heterogeneity (specification (3)), the decline is less steep. Figure 27 shows that, conditional on having at least one session, the average number of clicks in the first month of the unemployment spell is 4.83. The number declines by around 8%

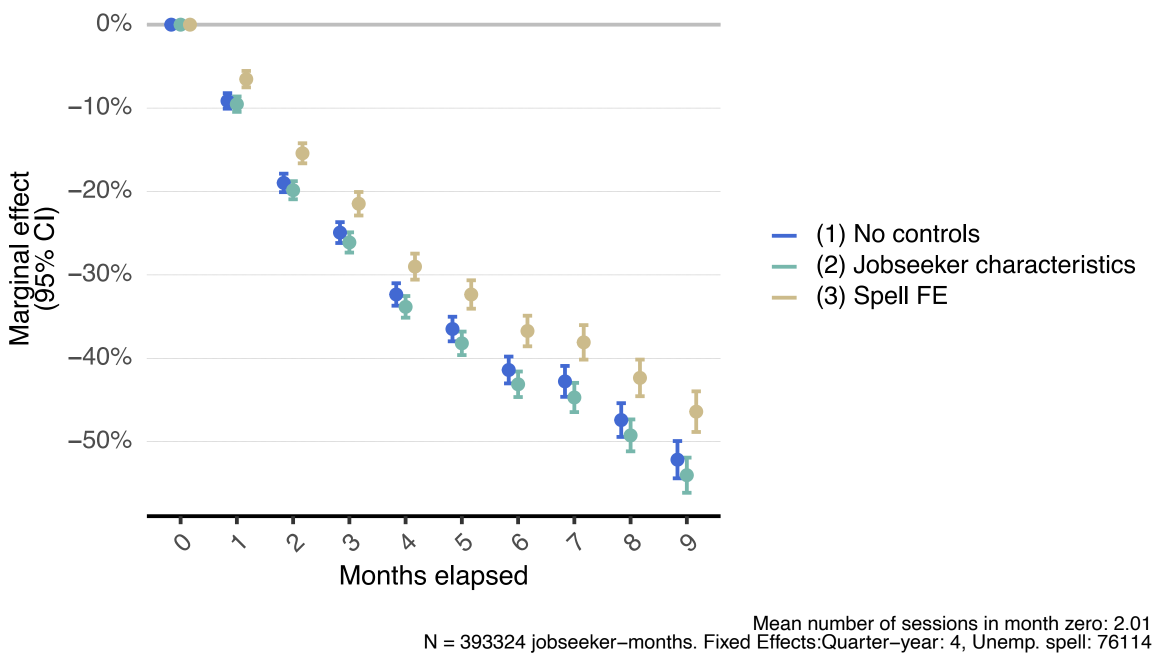

Figure 26: Poisson regressions of the number of session per elapsed month of unemployment spell. Marginal effects are shown. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

to around 4.6 clicks in the subsequent months. Once we control for unobserved heterogeneity, the number of clicks per session declines steadily over the search spell. This difference suggests that actually, jobseekers with longer spell durations tend to click on more vacancy postings per session. Appendix B Figure **??** looks at the number of clicks not over spell duration but over the order of sessions and shows very similar patterns.

Figure 28 shows the product of the clicks per session and the number of sessions; the cumulative number of clicks over the spell.

We also present some results where the outcome is the number of new clicks defined as the particular vacancy or the particular firm. Figure 29 shows how those two outcomes compare to all new clicks. The regressions are conditional on jobseeker-spell fixed effects, as in specification (3) above. Comparing spcification (1) and (2) of Figure 29 suggests that most new clicks are on vacancy postings that haven't been clicked on before and excluding the clicks on previously seen vacancies doesn't significantly change the path of clicks over time. However, specification (3) shows that the decline is sharper when we only consider clicks on firms that haven't been considered before. The slope of the decrease is around twice as steep as for the baseline specification. Overall, the results indicate that opportunities become more limited.

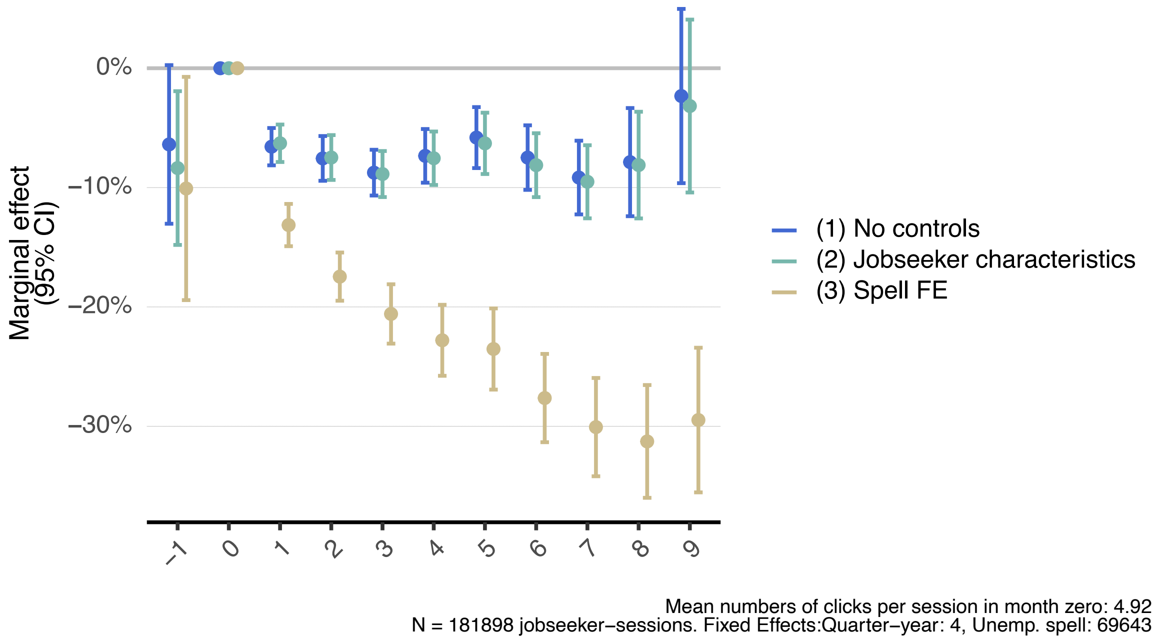

Figure 27: Poisson regressions of the average clicks per session on the elapsed month of unemployment spell. The regressions are conditional on having at least one session in a month. Marginal effects are shown. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

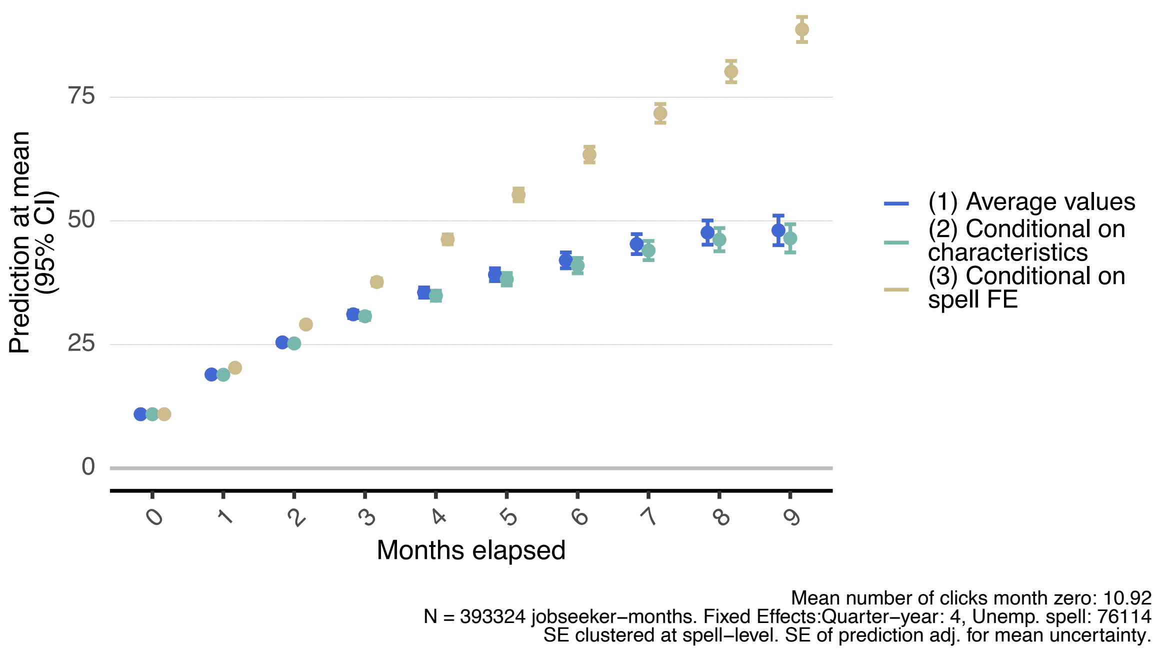

Figure 28: Predicted number of total clicks accumulated over the spell by jobseeker. Prediction from a Poisson regressions of the cumulated number of clicks on the elapsed month of unemployment spell. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

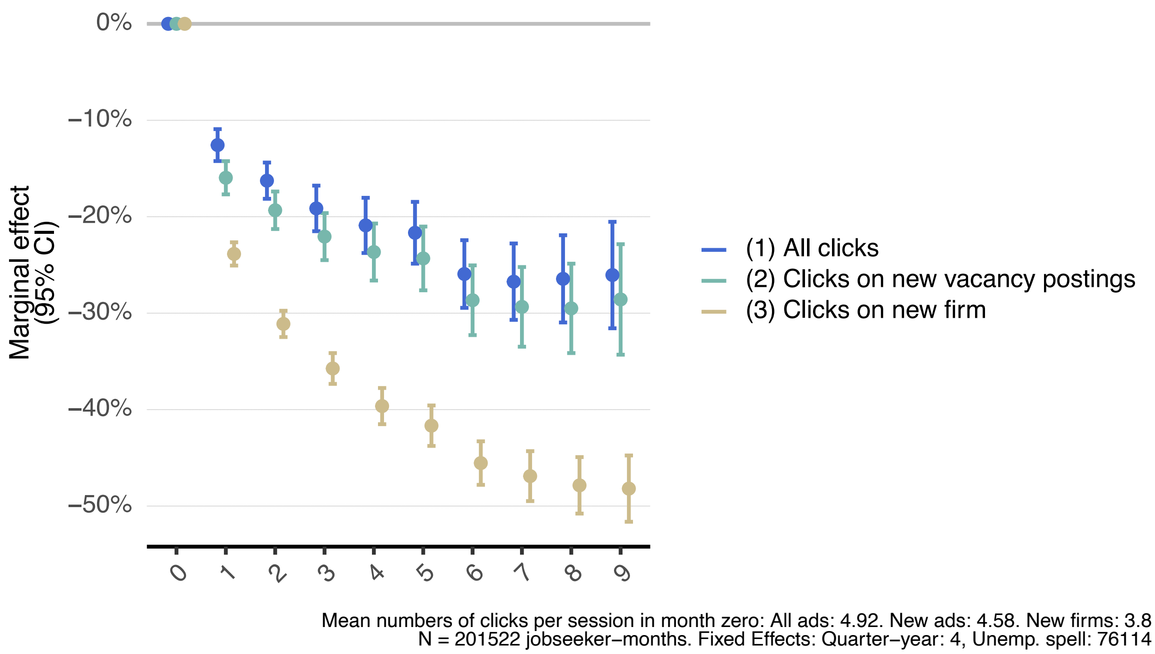

Figure 29: Poisson regressions of the average clicks per session on the elapsed month of unemployment spell. The regressions are conditional on having at least one session in a month. All regressions include jobseeker-spell fixed effects. Marginal effects are shown. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

CHAPTER 3

Adapting to Scarcity: Job Search and Recruiting Across Occupational Boundaries

Jeremias Klaeui, Daniel Kopp, Rafael Lalive, and Michael Siegenthaler*

May 2024

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.[1] 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.[2]

[1]The job portal only shows vacancies that exactly match the job seeker's search query. The search process is discussed in more detail in Section 3.1.

[2]As opposed to the job seekers, the recruiters not only see candidates whose work experience matches the occupation they search on the portal but also candidates who have no work experience but have declared upon registration

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. On average, 27% 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

with the unemployment services that they are willing to work in the searched occupation. We will exploit this institutional feature to identify recruiters' preferences for candidates with work experience in the searched occupation.

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).[3] Our study can help to im-

[3]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.

prove 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 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.[4] 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,[5] 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.

[4] 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.

[5] 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.

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' 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.[6] 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.[7].

[6] 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.

[7] 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

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 & 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.2 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 $\frac{2}{7}$.

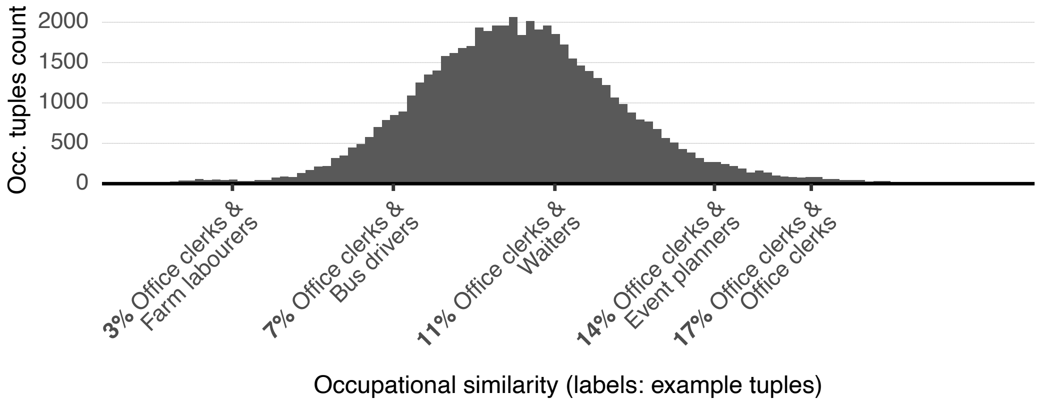
The second step in the construction of our overlap measure is to repeat step 1 for 5000 randomly drawn vacancy pairs[8] and then average the estimated Jaccard similarities over the randomly drawn pairs of job vacancies. We consider occupations with at least 200 posted vacancies between 2016 and mid-2022. 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

[8] 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.

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, 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%).

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

	General office clerks	Shop sales assistants	Manufactoring labourers	Waiters	Cleaners	Building construction labourers	Kitchen helpers	Cooks	Freight handlers	Stock and transport clerks
General office clerks	16.8	11.3	10.8	10.5	10.5	7.3	10.8	11.1	9	9.8
Shop sales assistants	11.3	17.1	9.7	12.8	12	5.5	10.5	10.9	8.4	8.6
Manufactoring labourers	10.8	9.7	15.9	9.1	11.5	14.1	12	12.2	14.1	12.7
Waiters	10.5	12.8	9.1	17	13.5	6.4	12.3	12.4	7.8	7.8
Cleaners	10.5	12	11.5	13.5	17.5	7.2	13	12.7	9.4	10.1
Building construction labourers	7.3	5.5	14.1	6.4	7.2	26	9.4	8	15.5	11.4
Kitchen helpers	10.8	10.5	12	12.3	13	9.4	18.8	12.7	10.7	10.4
Cooks	11.1	10.9	12.2	12.4	12.7	8	12.7	17.5	10.7	10.4
Freight handlers	9	8.4	14.1	7.8	9.4	15.5	10.7	10.7	17.2	14.5
Stock and transport clerks	9.8	8.6	12.7	7.8	10.1	11.4	10.4	10.4	14.5	16.3

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

3 Data

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

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.[9] This job platform is "Job-Room.ch". The click data from the platform 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.4 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.

To click on a job posting, the job seeker must enter a search term in the portal. If the job seeker wants to search for an occupation (the other options are locations or 'competencies'), the search term has to be selected from one of two lists of occupations that are suggested after typing at least two letters. The suggestion are a list of 333 ISCO-08 4-digit occupations and an internal list of 2428 more detailed occupations. We perform our analysis at the ISCO-08 4-digit level. All but two of the detailed occupations correspond exactly to one ISCO-08 occupation.[10]

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

[9] 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.

[10] We perform a counterfactual exercise to assess the quantitative importance of the two occupations that do not correspond one-to-one to an ISCO occupation: It could be that job seekers i) either want to search for their last occupation, but the jobs they click on are classified as a different ISCO occupation because of the ambiguity, or ii) that the job seekers want to search outside their last occupation, but the occupation is misclassified as their last occupation. Using the original classification, on average 26.62% of a job seeker's clicks are on jobs from their last occupation. Taking the extreme case that this actually happened in all cases where i) is possible would increase the proportion to 22.66%, and taking it that it actually happened in all cases where ii) is possible would decrease the proportion to 22.53%.

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)

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[11], those that likely represent temporary lay-offs[12], and very few job seekers with a last occupation with an insufficient number of vacancies to compute our occupational distance measure.[13] 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

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

[12]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.

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

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.3 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 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.[14] 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.[15] 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 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.[16]

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 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.

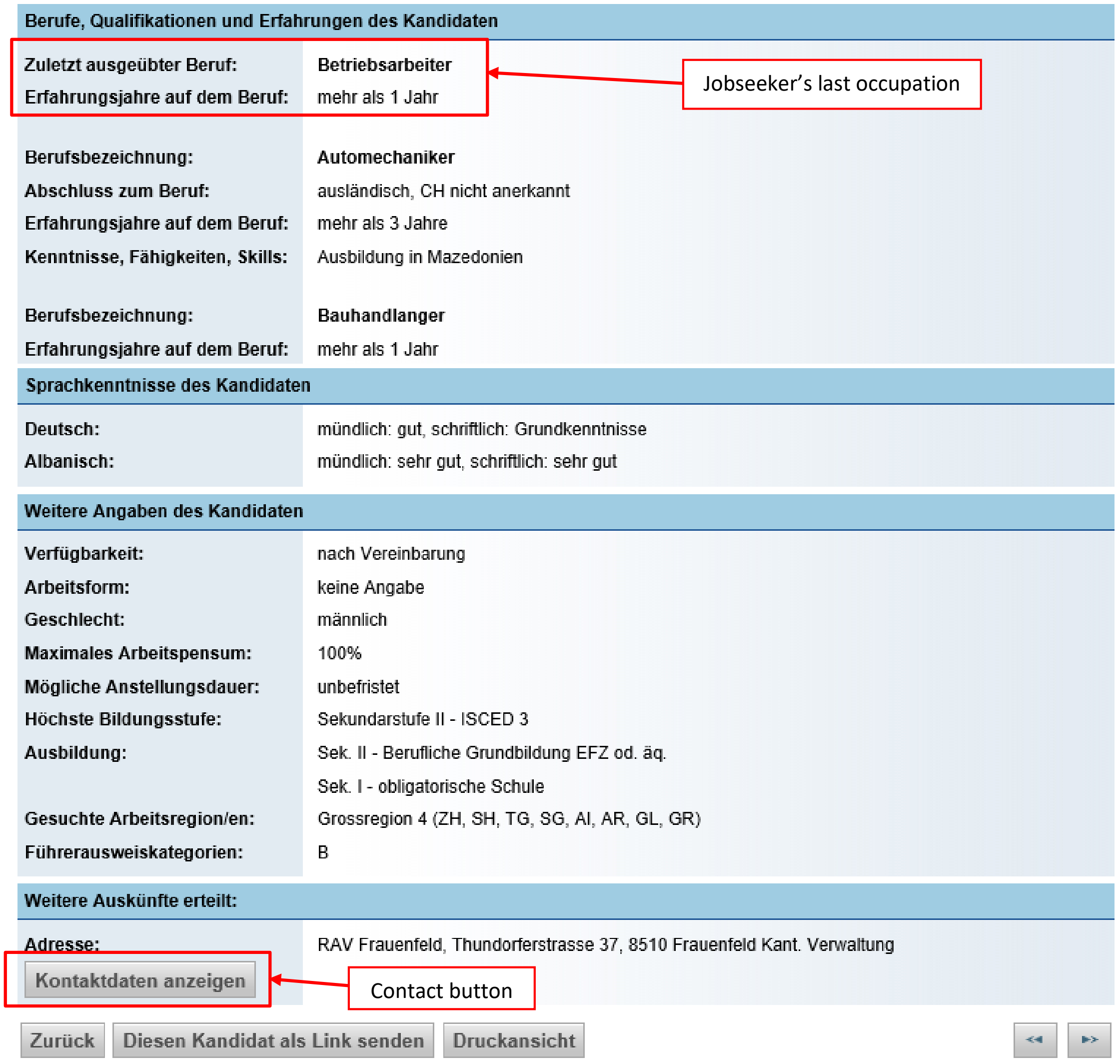
Table 2 presents key descriptive statistics of the recruiter sample. During the sample period from March to December 2017, 33,216 recruiters conducted a total of 317,123 searches. The database of the platform contained 173,638 distinct job seekers. In terms of occupational coverage, Figure A.5

[14] 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.

[15] 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.

[16] 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).

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.

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.

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.6 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.[17]

4 The role of overlap in job requirements

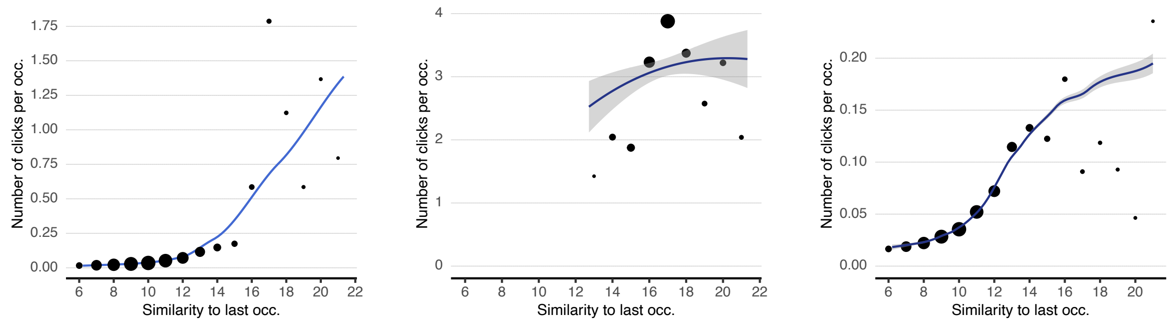
We are interested whether job requirement overlap is relevant in determining search across occupational boundaries on both market sides. This analysis also validates our measure of occupational distance, as the measure turns out to be highly predictive of the online search behavior of both jobseekers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

[17] The second Panel of Appendix Figure A.6 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.

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.

Using this dataset, Figure 4, panel a), shows a binned scatter plot of the number of clicks per occupation[18] 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' clicks even within job seekers' last occupation.

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

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.

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.[19] Both estimates are large in size.

[19] 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 click data and occupational similarity.

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[20] 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.[21] 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 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

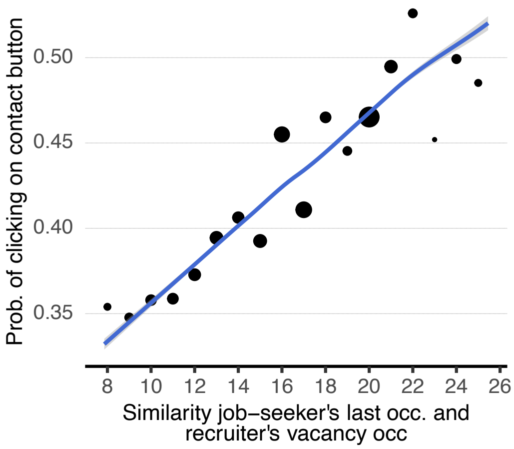
The previous section has demonstrated that job requirement overlap strongly predicts the occupations that registered job seekers target when searching for jobs on Job-Room. In this section we look at the labor demand side. How does the likelihood that recruiters contact job seekers depend on the job 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 proba-

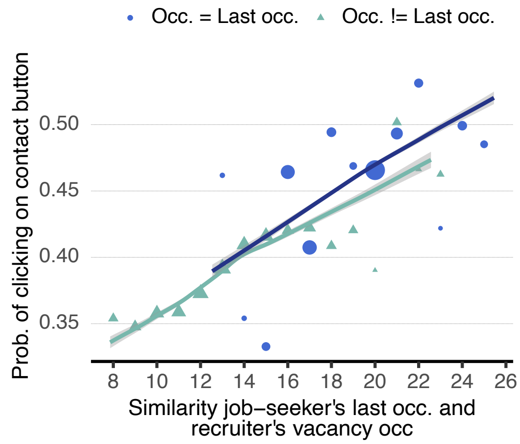
[20]We use median wages per ISCO 4-digit occupation as computed by merging the 2017–2019 waves of the Swiss Structural Surveys, which contain detailed occupation codes, to the 2018 wave of the Swiss earnings structure surveys, which contain highly reliable employer-reported hourly wages for a large number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

[21]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).

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.

bility that recruiters click on the contact button conditional on seeing a candidate profile (see Figure 3)[22]—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-

[22]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.

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.[23]

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' 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

[23] 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.

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.[24] 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

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

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).[25] 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 candidate on Job-Room. For recruiters who do not restrict their search regionally, the search region is defined as Switzerland as a whole.[26]

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.[27]

5.2 The effect of tightness in job seekers' last occupation

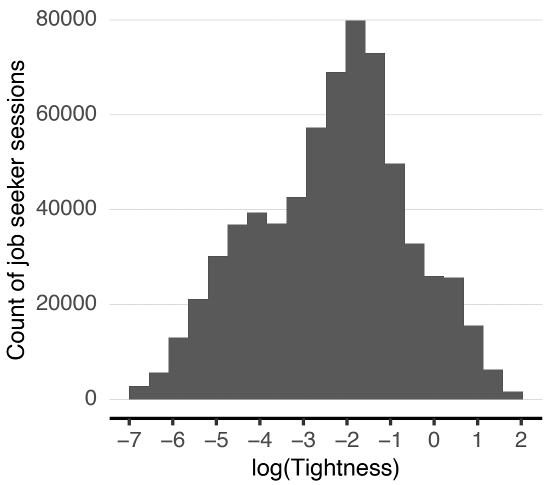
We first examine the effect of tightness in a job seeker's last occupation on her occupational search scope. We measure a job seeker's occupational scope with a relatively narrow and with a more encompassing outcome variable: i) the probability that a job seeker clicks on a vacancy in an occupation that 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,

[25] 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.

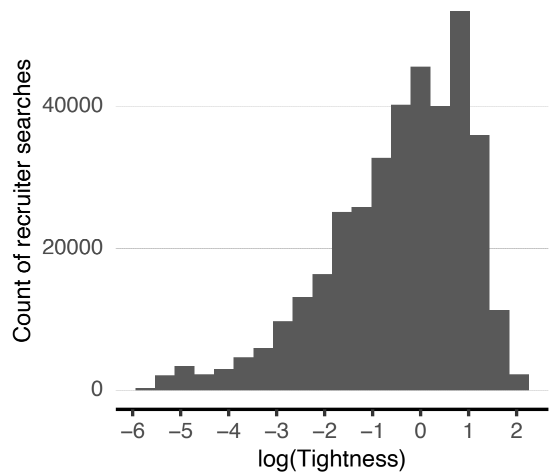
[26] Recruiters also have the possibility to do a search across all occupations, however only 1.3% of searches do not use occupation as a filter criteria. We omit those searches from our sample.

[27] 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.

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.

the broader is a job seeker's occupational scope.

Appendix Figure A.8 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: 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

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.

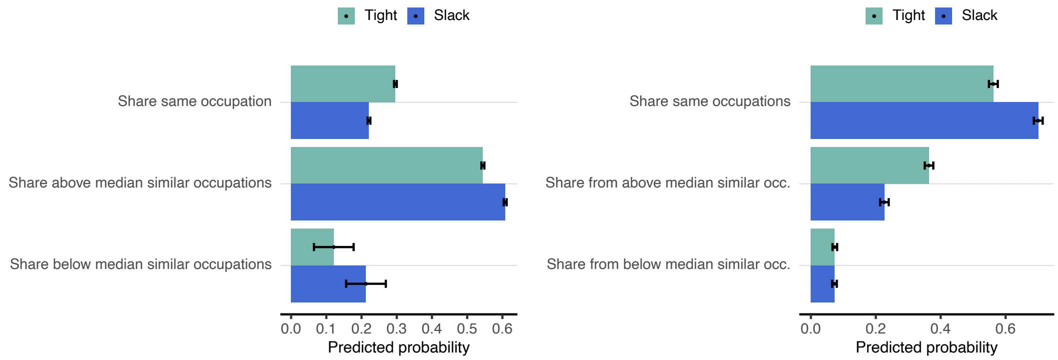
a job seeker fixed effect α_i, which controls not only for differences in a job seeker's last occupation and her cantonal search scope, but also for all time-constant (un)observed characteristics of a job seeker. We also control for the elapsed unemployment spell duration $\phi_{\tau(i,t)}$, as spell duration is a potentially important time-varying confounder.[28] 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 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

[28] 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.10 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.

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.

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).[29]

We can also use the estimates of other determinants of the occupational scope in Appendix

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

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.[30] 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 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.9 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

[30] 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.

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 fixed effects.[31]

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

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

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.

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 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.[32] 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 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.[33]

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

[32] 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.

[33] 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

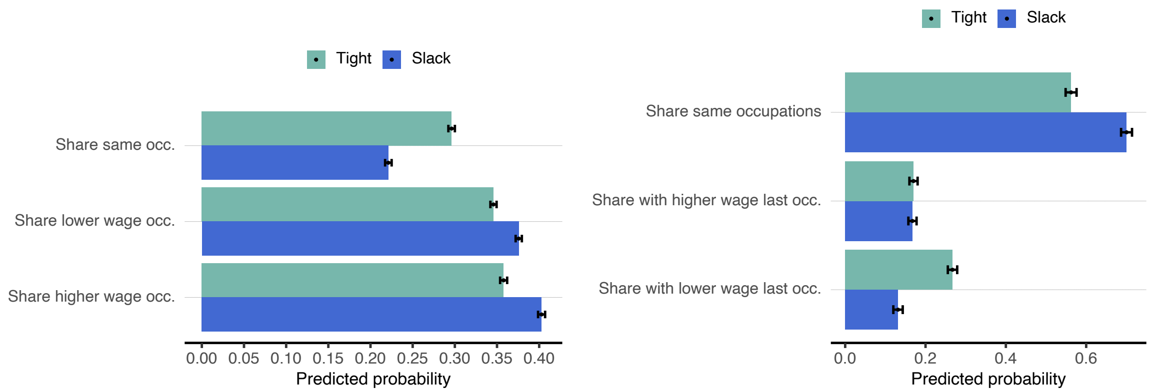
	Non-regulated last occ.		Regulated last occ.	
	(1)	(2)	(3)	(4)
Dependent Var.:	N clicked same occ	N clicked diff. occ	N clicked same occ	N clicked diff. occ
log(Tightness)	0.1082*** (0.0182)	-0.0240** (0.0119)	0.0192 (0.0680)	-0.0209 (0.0254)
Elapsed spell duration	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes
Job seeker (spell)	Yes	Yes	Yes	Yes
______________________	__________________	___________________	__________________	___________________
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
______________________________	___________________	____________________	___________________	____________________
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.

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.

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 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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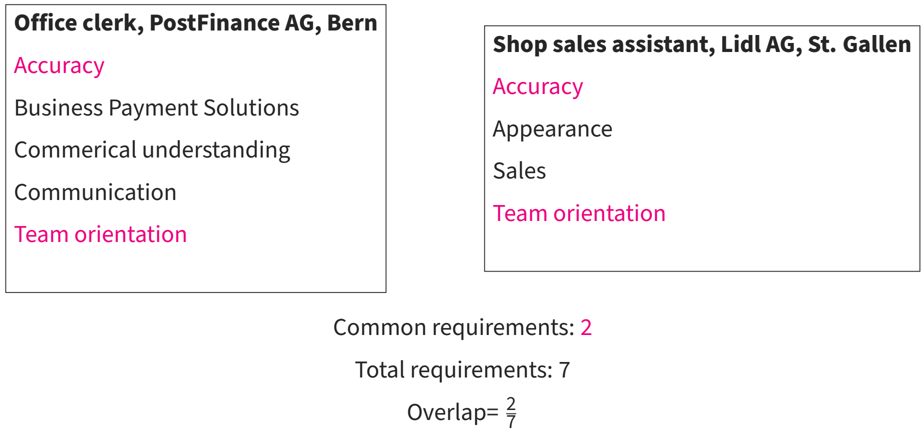
Figure A.1: Job Requirement Overlap Example



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

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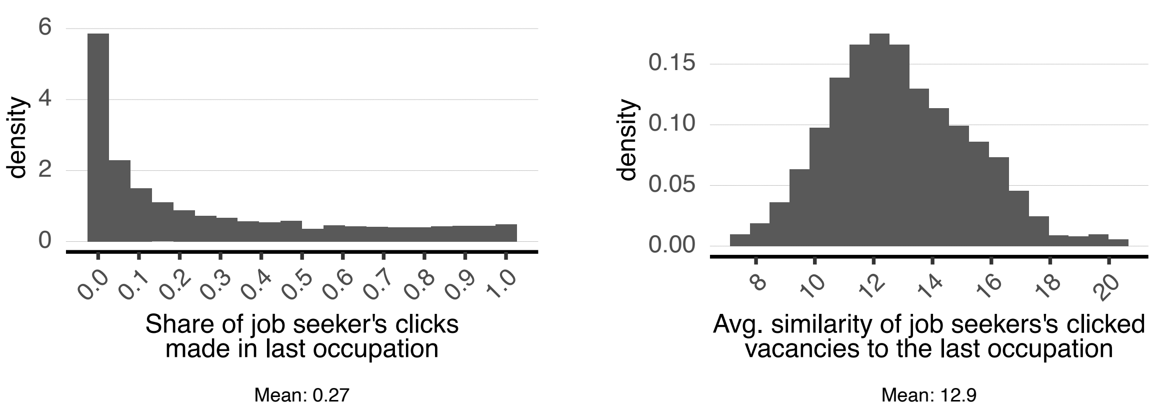
Appendix

Figure A.2: Job Requirement Overlap compared to the O*Net "Related occupations"

Notes: This graph shows a binned scatter plot showing the share of related occupations per bin. The binwidth is 2.5, and the dot's size represents the bin's number of observations. The "related occupations" classifications stems from the O*Net database and is the classification used by Belot et al. (2019) and Belot et al. (2022). We count occupations as related if they are assigned to the "primary" relation tier by O*Net, i.e the 10 most related occupations according to their calculations. The O*Net data is organized by the U.S. Standard Occupational Classification (SOC) system. To translate it to the ISCO system used in this study, the SOC 2019 occupations are merged to SOC 2010 occupations and subsequently to ISCO-08 4-digit occupations. The mapping is not one-to-one. We follow Belot et al. (2019) in using U.S. employment shares of the SOC 2019 occupations. For every ISCO-08 occupation pair we compute a weighted average of whether the occupations are related using the employment shares of the SOC 2019 occupations that map to the ISCO-08 occupations as weights. Source: X28, O*Net, Employment data from 2023 from the 2023 U.S. Bureau of Labor Statistics, own calculations.

Figure A.3: 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.

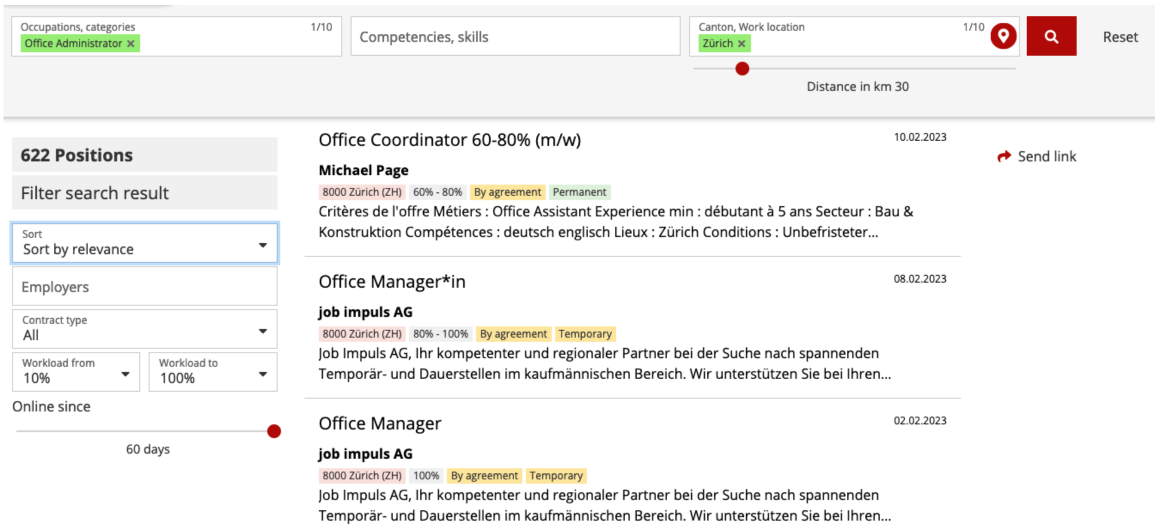
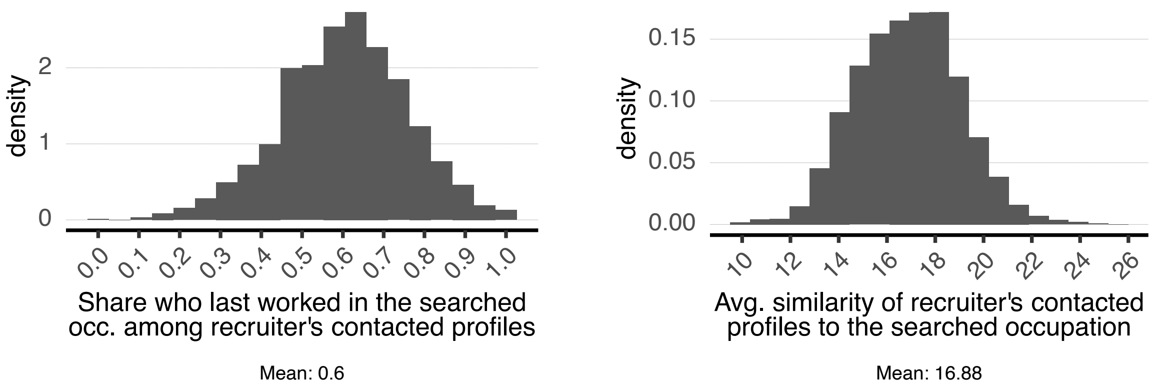


Figure A.4: Screenshot of the job platform of Job-Room.ch after entering "Office Administrator" and "Zurich" into the search mask

Figure A.5: 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.6: 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.

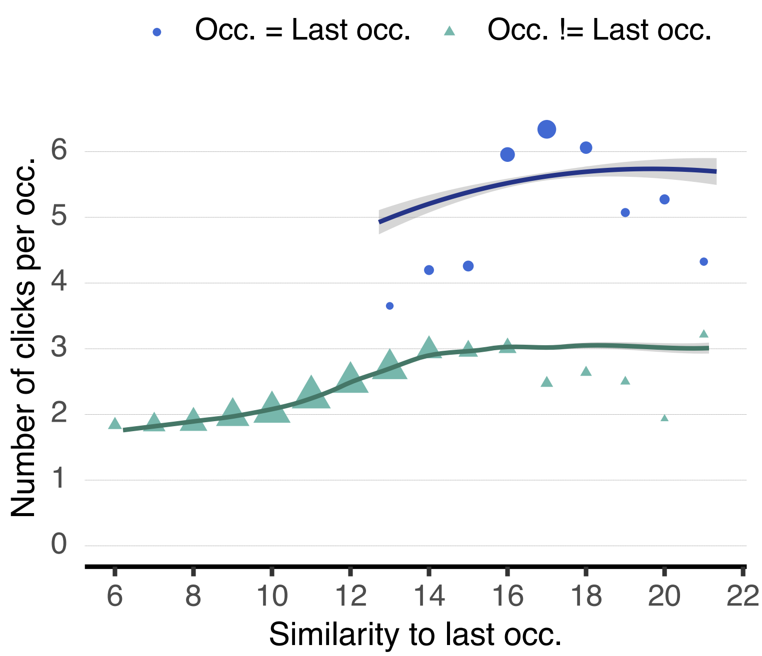
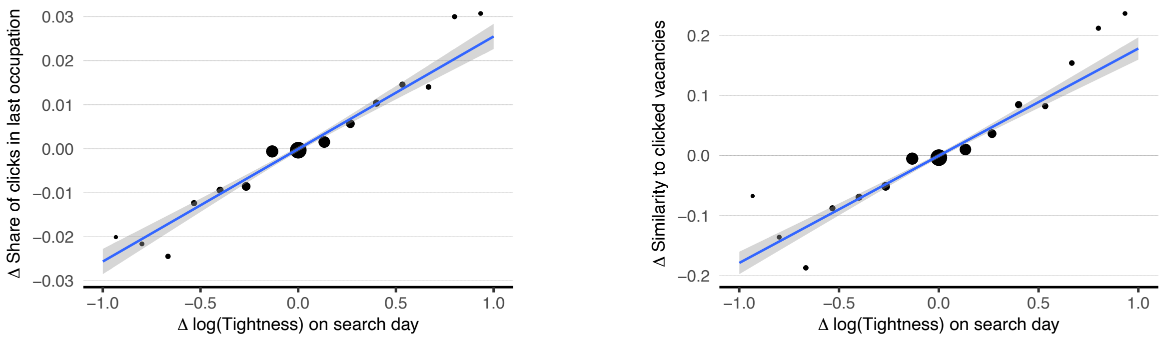


Figure A.7: Binned scatter plot with a local linear regression line: Correlation between the number of clicks in a given occupation, conditional on at least one click in the occupation, and the similarity between the occupation and the job-seeker's last occupation in a given month. The means per bin 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.8: Relationship between tightness in last occupation and occupational search scope of unemployed job seeker

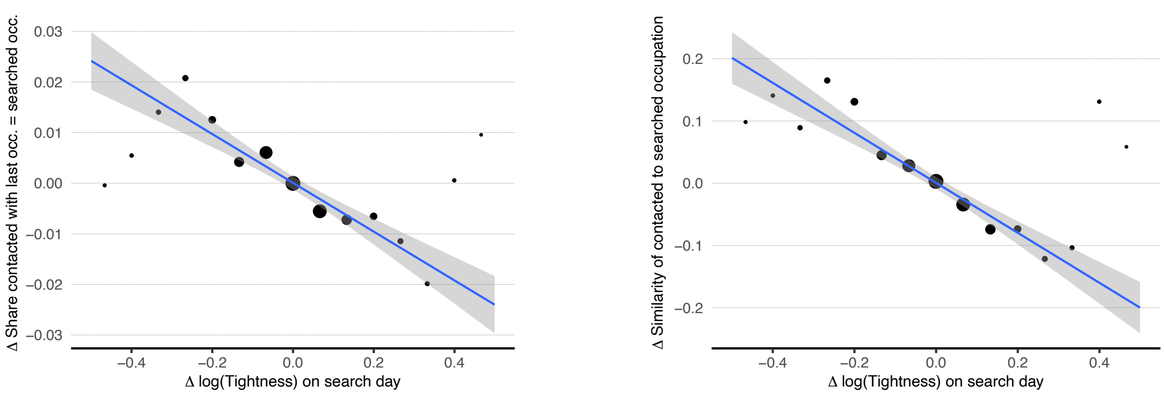


(a) Tightness in last occupation versus share of clicks in last occupation

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

Notes: Binnned 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.9: Relationship between tightness in a recruiter's searched occupation and his or her openness to occupational switchers

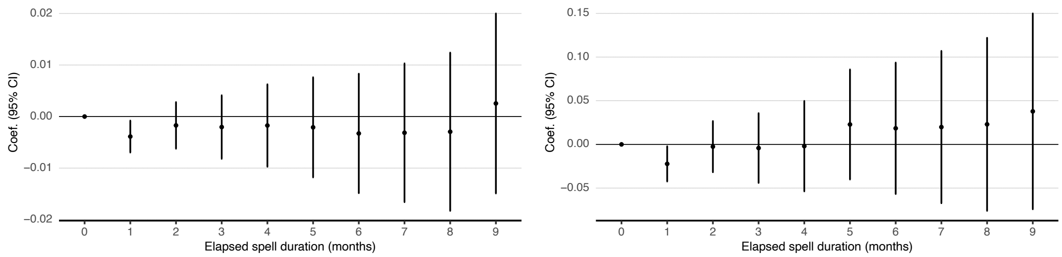


(a) Tightness in recruiters' searched occupation vs share of contacted candidates that last worked in recruiters' searched occupation

(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.10: 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.