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

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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 ($\pi$). 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 $\pi v$ 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 × location × 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

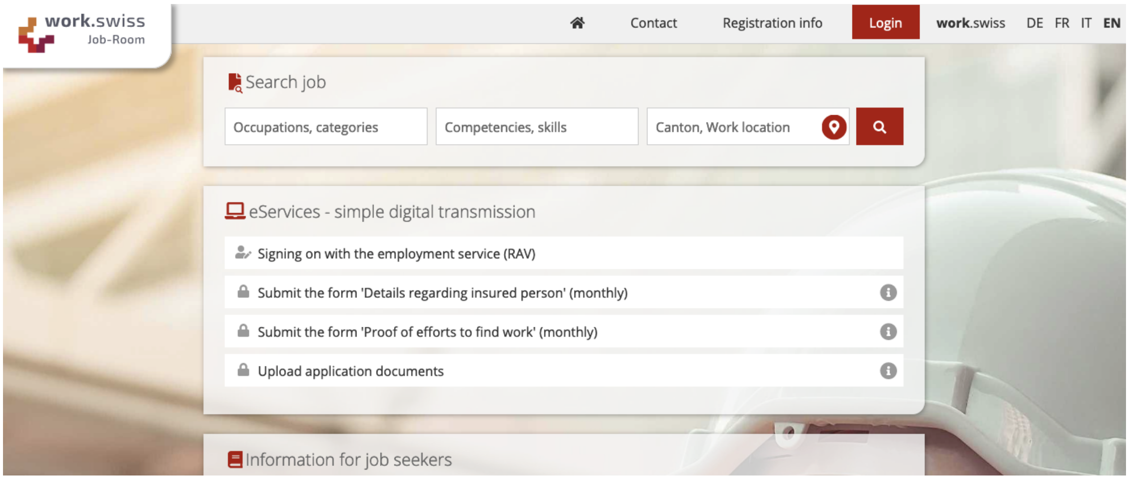



Figure 1: Screenshot job-room.ch.

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.

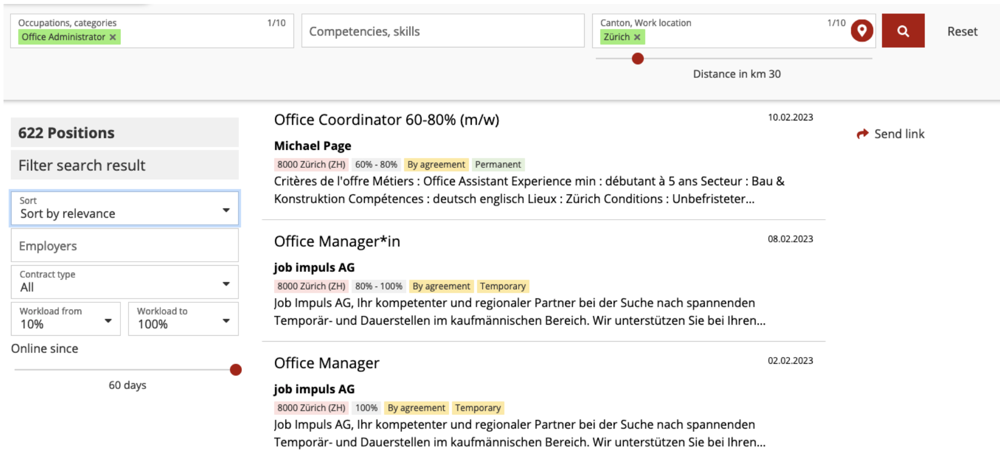



Figure 2: Screenshot of the result list when searching for "Office managers" in Zurich on the job room (`https://job-room.ch/home/job-seeker`). Screenshot taken 10-02-2023.

## 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.

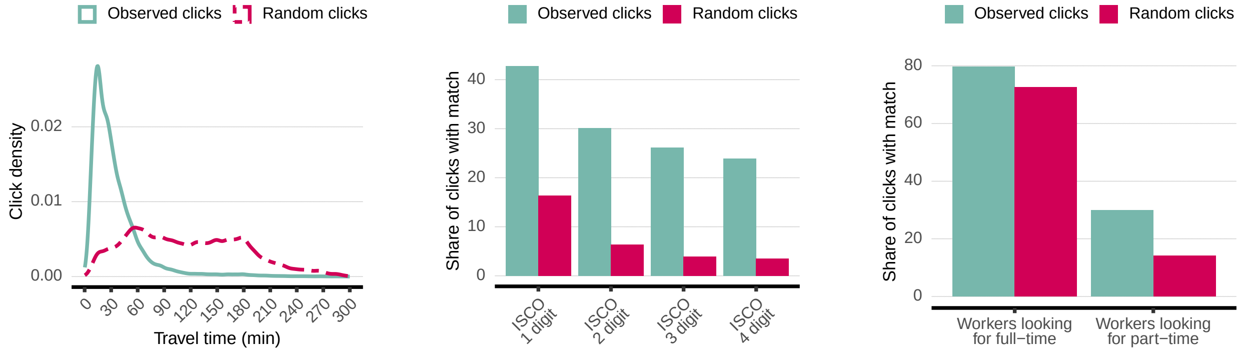
### 2.7 Descriptive evidence of targeted click behaviour

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 $\times$ occupation $\times$ 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, $O_{ij} = \mathbb{1}\left[\text{ISCO-08}_{\text{last job i}} = \text{ISCO-08}_j\right]$. 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, $H_{ij} = \mathbb{1}\left[\text{Part-time preference}_i = \text{Part-time}_j\right]$. The vacancy age is the (log) number of days the vacancy has been online at the time of the click.

$\delta_j$ 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 $\delta_j$ 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 $\delta_j$ 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, $\delta_m$. 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 $\delta_m$. The parameter $\lambda$ in Equation 2 measures the influence of the inclusive value on the submarket choice, reflecting the degree of correlation within submarkets. A lower $\lambda$ 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

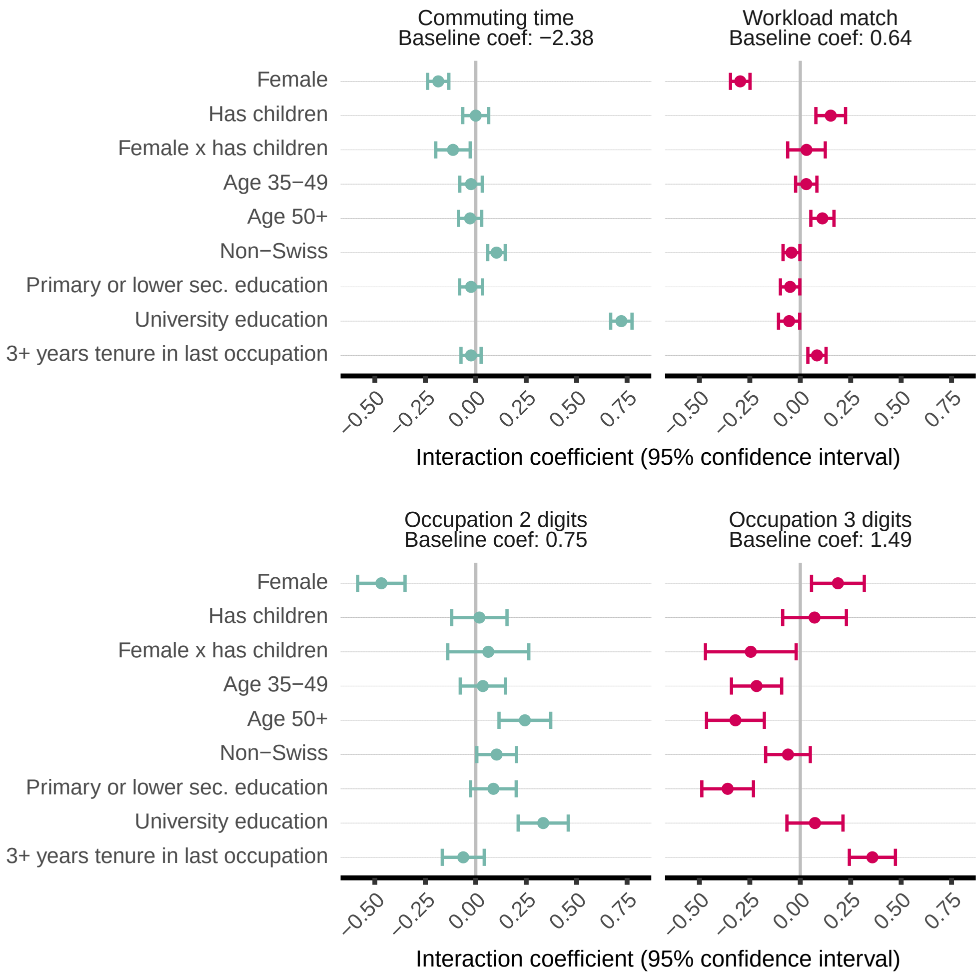
Figure 4 shows how the coefficient of the four match indicators vary with individual characteristics.

**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 $\beta$ 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$\vert X_i$) | 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 $\tau$ 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 $\gamma_1$, $\gamma_2$, ..., 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 $\zeta_1$, $\zeta_2$, ..., 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, $\mu_t$, accounts for economy-wide fluctuations in job finding probabilities. $X_{it}$ includes other covariates that may affect the exit probability. $\theta$ 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 $\mu_t$ 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

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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.

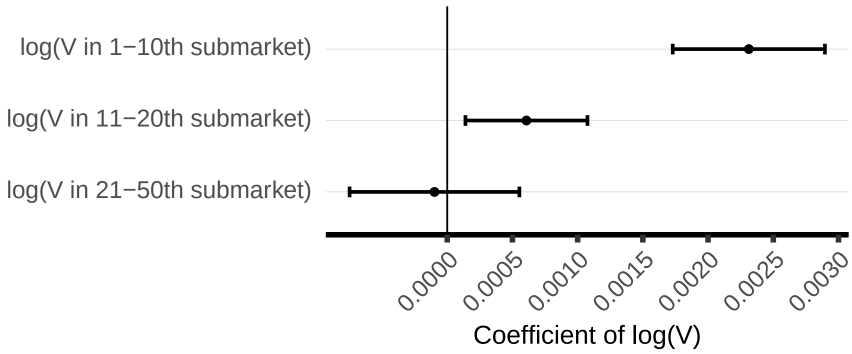
by approximately 0.42% relative to the baseline of 10.1%. This large positive coefficient is a puzzling finding. It is likely to be a feature of the fact that the consideration-probability weighting used in the computation of $U$ smoothes out a lot of variation over submarkets and that the stocks of 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.

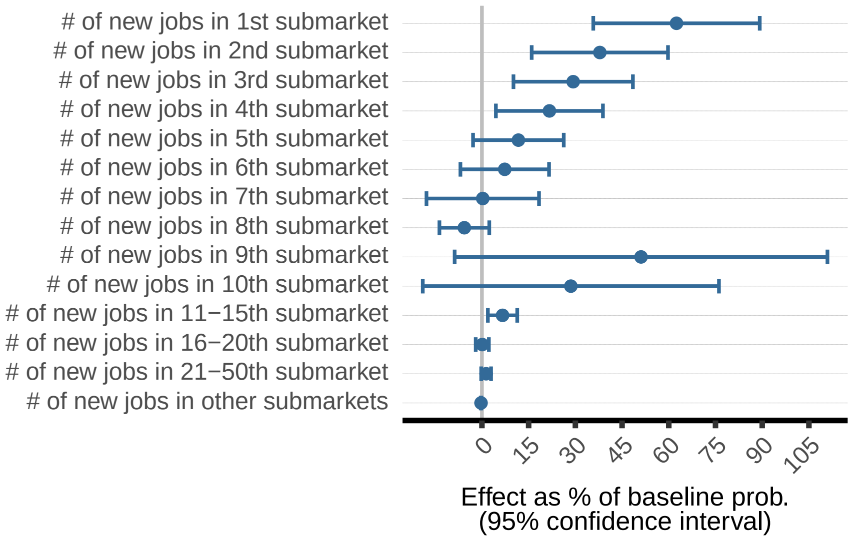
The magnitude of the estimates aligns very closely with the estimates from the baseline specification: if one converts the baseline effects of the log number of active vacancies to a average marginal effects, one finds that 1 additional vacancies in the ten most preferred submarkets increase the exit 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.

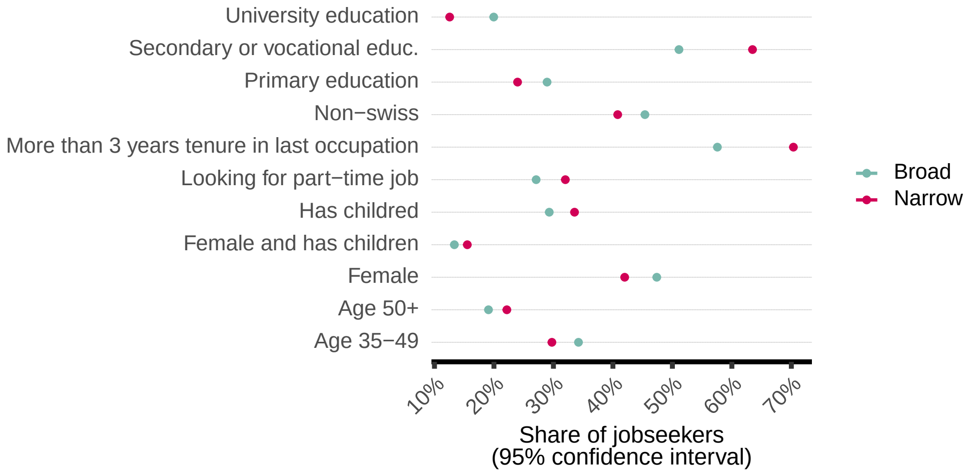
If this probability is high, it means that the first 10 markets have a high share in the total consideration relative to the other markets. For the median jobseeker, the share of consideration that goes to the first 10 submarkets is 8.0%, for a very 'broad' jobseeker the share is 5.1% (10th percentile) 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.

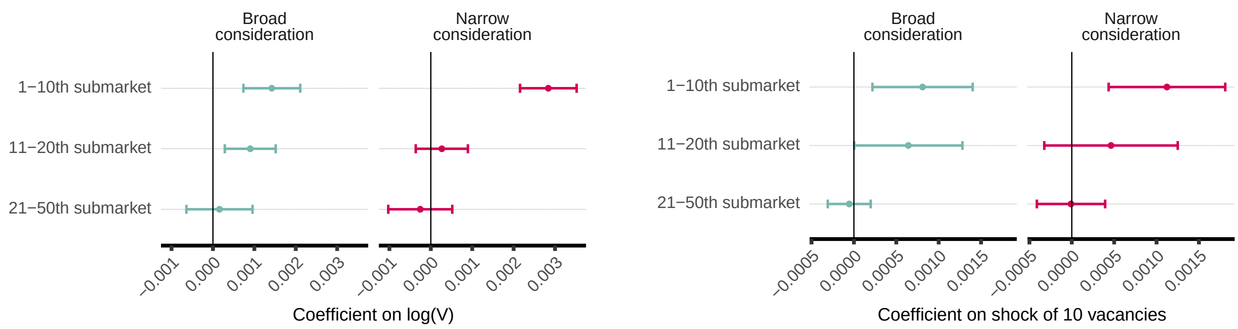
In Panel (b), the estimates based on mass-hiring shocks offer a parallel yet less precise reflection of the patterns observed in Panel (a). The effect of hiring shocks in the 10 most preferred submarkets is larger for jobseekers with a narrow consideration scope, although the difference is not statistically 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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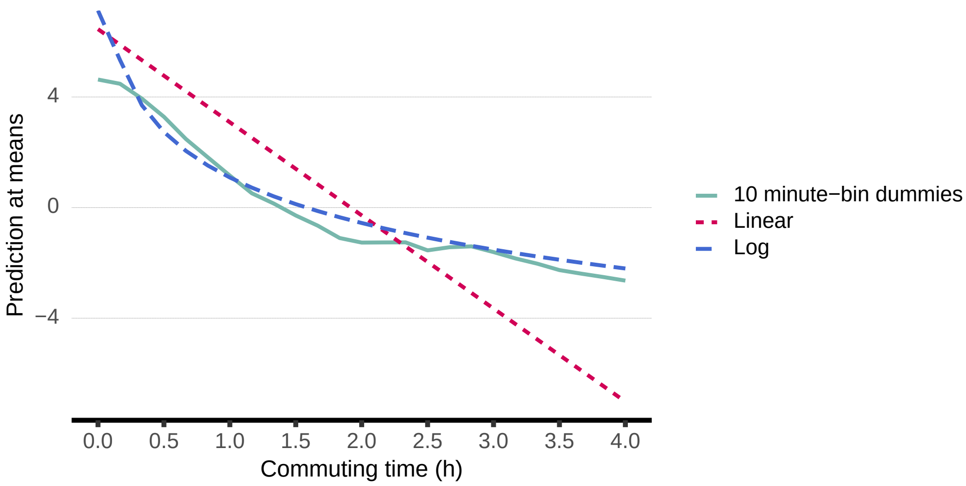
Figure 9: Functional form of the effect of the commuting distance on job consideration




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 |

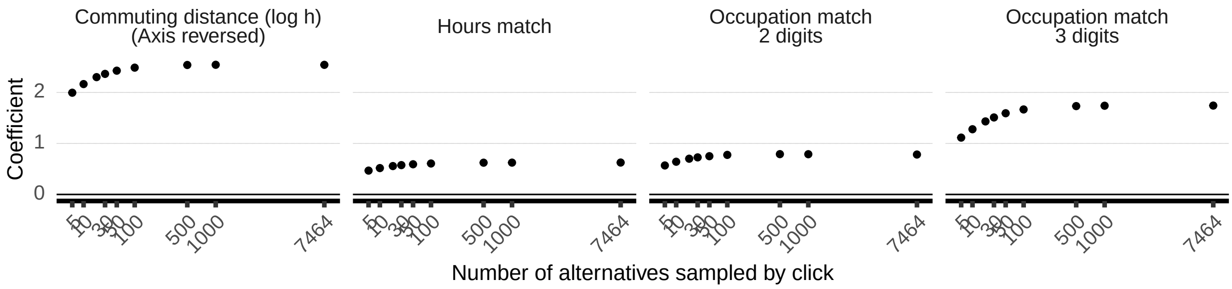
Table 9: Effect of a mass-hiring event on finding a job at the hiring firm. The estimates are form an OLS regression of a binary variable indicating whether the individual found a job at the hiring firm within 12 months of the hiring shock. One observation is a jobseeker-shock pair. The explaining variables 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

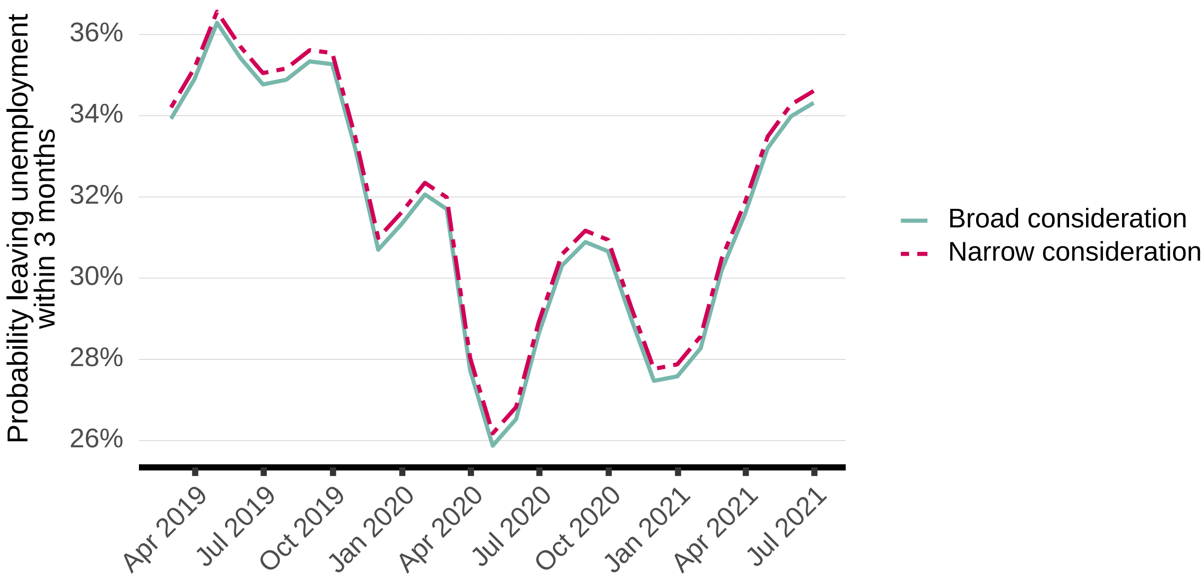



Figure 12: The simulation depicted in Figure 9 contrasts the unemployment exit probabilities between jobseekers with broad versus narrow consideration scopes, using the real distribution of vacancies. It differentiates jobseekers by the breadth of their job search, categorized as "narrow" for those focusing 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).