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ABSTRACT

Helping Jobseekers with Recommendations Based on Skill Profiles or Past Experience: Evidence from a Randomized Intervention*

Searching for jobs is challenging, and online platforms now often offer tailored job recommendations. In a randomized controlled trial with over 1,250 participants, we evaluate recommendations based on prior experience and based on skill profiles assessed at study enrolment, respectively. We find that on average both types of recommendations improve job finding rates. Profile-based recommendations are especially effective for individuals with limited experience and mismatch in the prior job, while experience-based recommendations may slower job finding for those with limited experience but a well-matched previous job. These findings highlight the need to align job search advice with jobseekers' skills.

JEL Classification: J24, J62, J64

Keywords: jobseekers, online job search, occupation recommendations

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1 Introduction

Job seeking is a challenging activity as it requires collecting information and making difficult decisions about vacancies worth applying to. The literature shows that a common strategy is to look for jobs in the occupation one was employed before unemployment (Belot *et al.*, 2018). The validity of such a strategy depends on many factors, e.g., whether the previous job was a good match for one's skill profile, how much occupation-specific human capital one has accumulated and, of course, the level of labour demand.

In this paper, we evaluate a randomized controlled intervention in which we tested alternative forms of individualized online advice about occupations to consider in job search. We created an online job search platform named *Job for You* (J4U) and parametrized it to provide recommendations based on proximity to either the jobseeker's skill profile or the jobseeker's previous job. We measure individual skill profiles using tests and questions given to all study participants during the enrolment process and use O*NET to measure skill requirements in occupations to compute proximity. We randomly assigned participants to two treatment arms, one in which recommendations are based on the skill profile – we label this treatment *profile-based* – and one in which recommendations are based on the previous job that we label *experience-based*. We also have a control group consisting of randomly allocated participants who have access to a simplified version of the J4U platform without any recommendations.

Recruitment of study participants took place in collaboration with the Public Employment Services in the Swiss canton of Zurich between September 2022 and June 2023. Registered jobseekers were invited to participate by signing up on our J4U platform. When registering on the platform, they were randomly assigned to one of the two treatment groups or the control group with equal probability. The enrollment process included a comprehensive baseline questionnaire in which, together with a number of questions about the jobseekers' socio-demographic characteristics and previous labour market history, we assessed 12 skills and competences.[1] The assessment was developed by a team of psychologists and closely corresponds to how these 12 items are measured in O*NET, allowing us to compute measures of distance between the individual skill profiles and occupation requirements.

In addition to the information collected via the baseline questionnaire, we also have detailed data on the usage of the J4U platform, such as login times and clicks on specific vacancies. Furthermore, a collaboration agreement with the Swiss Federal Statistical Office and the Swiss State Secretariat for Economic Affairs allows us to link our self-collected

[1] For a discussion of how these 12 items where selected and measured, see Aschwanden *et al.* (2023) and Bächli *et al.* (2024).

data with information from administrative records on job search. We can therefore follow participants for eight months from the date of study registration and know whether and when they have found a job (or de-registered from the employment office for other reasons) and in which occupation.

When looking at the entire sample of participants, our results show that both the profile-based and the experience-based occupation recommendations have a positive but statistically insignificant effect on job finding. However, there is important heterogeneity across subgroups. There is a difficult trade-off when considering a change of occupation, namely the risk of losing the occupation-specific human capital accumulated in previous jobs versus the potential benefit of a more suited occupation. Using our skill assessment, we can compute proximity between the jobseekers' skill profiles and the requirements in their previous jobs and thus identify individuals who were well or poorly matched in their previous job. We show that the profile-based treatment significantly increases job finding for workers who were employed in bad matches and with low experience in their previous jobs. These workers have little occupation-specific human capital to lose and could benefit greatly from moving away from an occupation that does not match their skills. In all other subgroups we do not detect statistically significant differences in job finding compared to the control group. However, the participants in the profile-based treatment tend to perform generally better than those in the experience-based treatment.

Job search takes place mostly online (see Faberman and Kudlyak, 2016; Kircher, 2020, for an overview), generating a wealth of information that jobseekers need to process. A number of studies have conducted experiments on existing public platforms in Denmark (Altmann *et al.*, 2022), France (Ben Dhia *et al.*, 2022; Bied *et al.*, 2023), U.K. (Belot *et al.*, 2018), Sweden (Barbanchon *et al.*, 2023). Contrary to our experiment, which uses measured skill profiles independent of occupation history and education degrees, most previous studies that provide occupation recommendations to jobseekers are largely based on past occupation choices or labour market conditions. For example, the online advice provided by Belot *et al.* (2018) is based on actual occupation mobility data or on matrices from O*NET about transferable occupations. Similarly, Altmann *et al.* (2022) use actual occupational mobility data to suggest occupations that jobseekers may not otherwise consider. Barbanchon *et al.* (2023) use clicks of job ads recorded on an online job search platform to inform about the state of demand and supply in different occupation- or location-specific labour markets. Bied *et al.* (2023) also provide jobseekers with information about labour market conditions but they do so using Machine Learning techniques. They estimate and communicate to the jobseekers the hiring probabilities in specific vacancies predicted using actual hirings, job postings and individual characteristics. The work of Carranza *et al.* (2022) is more closely aligned with our approach as they also directly assess jobseekers's skills. Their experiment disseminates information about skill profiles to either only workers alone or both workers and potential employers. However, unlike our study, they do not match skill profiles to suitable job vacancies.

We contribute to this literature by further personalizing job advice using measured skills and contrasting the effects of profile-based and experience-based recommendations. Creating job search advice solely based on past labour market experiences and labour market conditions fails to acknowledge the considerable mismatch that exists in all labour markets (Şahin *et al.*, 2014). Workers who become unemployed from (and perhaps because of) a job in which they were badly matched may not benefit much from recommendations of vacancies in similar occupations. Changing occupation is a difficult decision that involves assessing the trade-off between accumulated human capital that is specific to an occupation and the quality of the match with jobs in the occupation. Consistently with this view, we find that the profile-based treatment is particularly effective for workers who can benefit the most from moving away from their previous jobs.

The remainder of the paper is structured as follows. Section 2 outlines how the study is set up and Section 3 provides information about the data. Section 4 presents our findings followed by a discussion in Section 5. Section 6 concludes.

2 Study setup

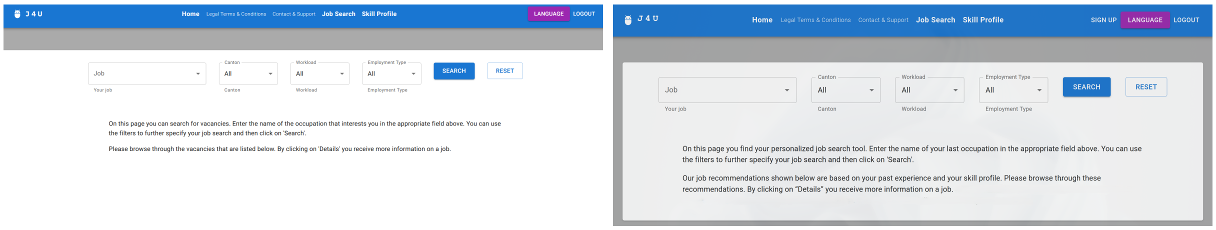
The core of our randomized controlled trial (RCT) is an online job search platform that we named *Job for You* (J4U). We developed J4U to provide the jobseekers participating in our study with customised occupation recommendations with the corresponding vacancies. The RCT consists of two treatment arms, one that we label *experience-based treatment* and the other one *profile-based treatment*, and a control group. The two treatments differ in the way the platform recommends occupations. The experience-based approach uses the jobseeker's previous job experience, while the profile-based approach mostly uses information about the jobseeker's actual skill profile, measured at baseline. This section describes the design and the functioning of the platform, the study setup, the treatment arms and the recruitment of participants.

2.1 Platform "Job for You" (J4U)

We developed the online platform *Job for You* (J4U), available in German and English, to provide participating jobseekers with customized recommendations about occupations and

Figure 1: Job search page

(a) Control group (b) Experience- and profile-based groups



Note: Panel (a) shows the job search page of the control group and Panel (b) of the experience-based and profile-based groups. The field "Job" contains a drop-down menu with ISCO 4-digit occupation names. The field "Canton" contains a drop down menu with all 26 Swiss cantons. The field "Workload" contains a drop-down menu with the following options: All, Full-Time, Part-Time. The field "Employment Type" contains a drop-down menu with the options All, Permanent, Temporary.

vacancies.[2] The platform could be accessed from any internet-connected device. Having our own platform allowed us to accurately track job search behaviour by observing and recording all the activities performed on the platform.

The J4U platform pooled vacancies from the official repository of the Swiss State Secretariat for Economic Affairs (SECO), which is the same source used by case workers at public employment services for their counselling activities (`www.job-room.ch`). This repository contains job advertisements that are notified by employers to the local office of the public employment service. Employers can also freely post their vacancies in the online repository. In addition, a specifically developed API by the SECO regularly scrapes the internet, i.e. other commercial job search platforms and the websites of private companies, to add further job announcements to the repository. Eventually, although *job-room.ch* does not cover the universe of all available job advertisements, it offers a rather comprehensive source of vacant jobs in Switzerland.

The core of the J4U platform is the job search page and it comes in two versions. The users in the control group were presented with the interface shown in Panel (a) of Figure 1. They were instructed to select the occupation they were interested in from the drop-down menu to see the corresponding available vacancies. The experience-based and profile-based groups were given access to the extended interface shown in Panel (b), where they could select their previous occupation and obtain occupation recommendations produced with the treatment-specific algorithm that we describe below. In addition, participants in all groups could restrict their search by indicating a specific canton (there are 26 cantons in Switzerland) and contract type (permanent or temporary and part-time or full-time).

When clicking on the search button, the platform displayed occupations and vacancies

[2]The platform was developed based on an earlier version, which was used in two RCTs conducted in the Swiss French speaking cantons of Neuchâtel and Vaud (Benghalem *et al.*, 2023).

presented in different ways depending on treatment. For the control group, the platform simply showed the available vacancies in the chosen occupation. For the experience-based and profile-based treatments, instead, vacancies were presented grouped by occupations and occupations were ranked by proximity to the user's previous experience or actual skill profile, respectively. In both cases, we rely heavily on the well-known database O*NET (www.onetonline.org). O*NET is an archive of occupational descriptions. For over 1,000 occupations, O*NET provides over 450 descriptors, such as reading comprehension or inductive reasoning, categorized into domains such as skills, abilities, work styles, educational requirements, values.

For each occupation and descriptor, the database contains quantitative indicators of the importance and the required level of competence. For example, for dental hygienists "near vision", a descriptor in the domain of abilities, is assigned an importance indicator equal to 4 on a scale 1 to 5, whereas "night vision" is equal to 1. Out of all the O*NET descriptors, we selected twelve items whose importance score are at the same time sufficiently high in most occupations and sufficiently heterogeneous to allow discriminating across occupations. A third important criterion that we adopted in the choice of these items was that they could be measured at the level of the individual jobseeker using scientifically established tools that could be incorporated into a relatively short online assessment exercise. Eventually, the selected items are:

- <u>Adaptability</u>: being open to change (positive or negative) and to diversity in the workplace;
- <u>Tolerance to stress</u>: accepting criticism and dealing calmly and effectively with high-stress situations;
- <u>Leadership</u>: willingness to lead, take charge, and offer opinions and direction;
- <u>Self-control</u>: maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behaviour, even in very difficult situations;
- <u>Reading comprehension</u>: understanding written sentences and paragraphs in work-related documents;
- <u>Time management</u>: managing one's own time and the time of others;
- <u>Monitoring</u>: monitoring and assessing the performance of yourself, other individuals, or organizations to make improvements or take corrective action;
- <u>Fluency of ideas</u>: ability to come up with novel ideas about a topic;

- Memorization: remembering information such as words, numbers, pictures, and procedures;
- Inductive reasoning: combining pieces of information to form general rules or conclusions;
- Category flexibility: generating or using different sets of rules for combining or grouping things in different ways;
- Perceptual speed: ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns.

At the time of study enrolment, we administered to each participant a baseline questionnaire that included an online assessment of these twelve descriptors. In two companion papers, we describe both the selection of the items and the online assessment in detail (Aschwanden *et al.*, 2023; Bächli *et al.*, 2024). For the purpose of this paper, we want to emphasise two features of the selected descriptors. First, despite the selection being partially arbitrary, the twelve items capture differences across occupations very effectively. Figure 5 in Bächli *et al.* (2024) shows that distances across occupations computed using all available O*NET descriptors highly correlate with distances computed using only the selected descriptors. Second, the online assessment was designed to guarantee the comparability of the resulting individual scores with the O*NET indicators. Thus, we can use the individual scores that we obtain at baseline to construct meaningful measures of distance between each jobseeker's skill profile and each occupation.[3]

For each jobseeker we know the occupation of the job they held before unemployment and we can compare the O*NET descriptors of the previous job with those of any other occupation. More formally, for the experience-based treatment we compute the Euclidean distance between each jobseeker's previous occupation and any other occupation o according to the following formula:[4]

$$d^E(i,o) \quad = \quad \frac{d^s(o_i,o) + \frac{1}{9}\sum_{k=1}^{9} d^k(o_i,o)}{2} \tag{1}$$

where i indicates the jobseeker, o indicates the occupation and o_i is the previous occupation.

[3]O*NET is originally designed to describe occupations in the context of the US labour market. Nevertheless, a number of studies have shown that it also works well for other industrialised countries, including Switzerland (Hanna *et al.*, 2019; Forstmeier and Maercker, 2008).

[4]In practice, the platform uses the occupation that jobseekers indicate in the field "Job" (see Figure 1) as the previous occupation when computing the distance in equation 1.

The functions $d()$ are all Euclidean distances between occupations computed using the indicators of the O*NET descriptors organised by domains.[5] There are nine O*NET domains that we consider and we group the twelve descriptors that we selected for the individual assessment together into a separate domain s.[6] Each $d^k(o_i, o)$ is the Euclidean distance between occupation o_i and occupation o based on the O*NET scores of the descriptors in domain k. Similarly, $d^s(o_i, o)$ is the Euclidean distance between occupation o_i and occupation o based on the O*NET scores of our twelve selected descriptors.

Importantly, all distances in equation 1 are fully based on O*NET data.[7] This is in contrast to the profile-based treatment where the distance $d^s(o_i, o)$ is computed using the individual scores measured in the baseline assessment according to the following equation:

$$d^P(i, o) \quad = \quad \frac{d^s(a_i, o) + \frac{1}{9}\sum_{k=1}^{9} d^k(o_i, o)}{2} \tag{2}$$

where the symbols have the same meaning as in equation 1 and a_i refers to the individual scores from the online assessment.[8]

The J4U platform presents occupations ranked by $d^E(i, o)$ for jobseekers in the experience-based treatment and by $d^P(i, o)$ for those in the profile-based treatment. In the first case, the recommendations are based exclusively on one's previous job experience. By design, the first ranked occupation is that of the jobseeker's previous job and the following occupations are the most similar ones according to the O*NET descriptors. Hence, the experience-based treatment is similar to other recommendation interventions that have been previously implemented in the literature (e.g., Belot *et al.*, 2018). The profile-based treatment, instead, ranks occupations mostly based on the individual jobseeker's assessed scores in the twelve selected descriptors and, to the best of our knowledge, it is a recommendation intervention

[5]The exact O*NET indicators that we use vary depending on the descriptor. For descriptors in the domains of Skills and Abilities, we use the level scale because this is the indicator that is the most comparable with the scores of the online assessment exercise. For descriptors in the domain of Work Styles we use the importance scale because it is the only one available in O*NET for these items.

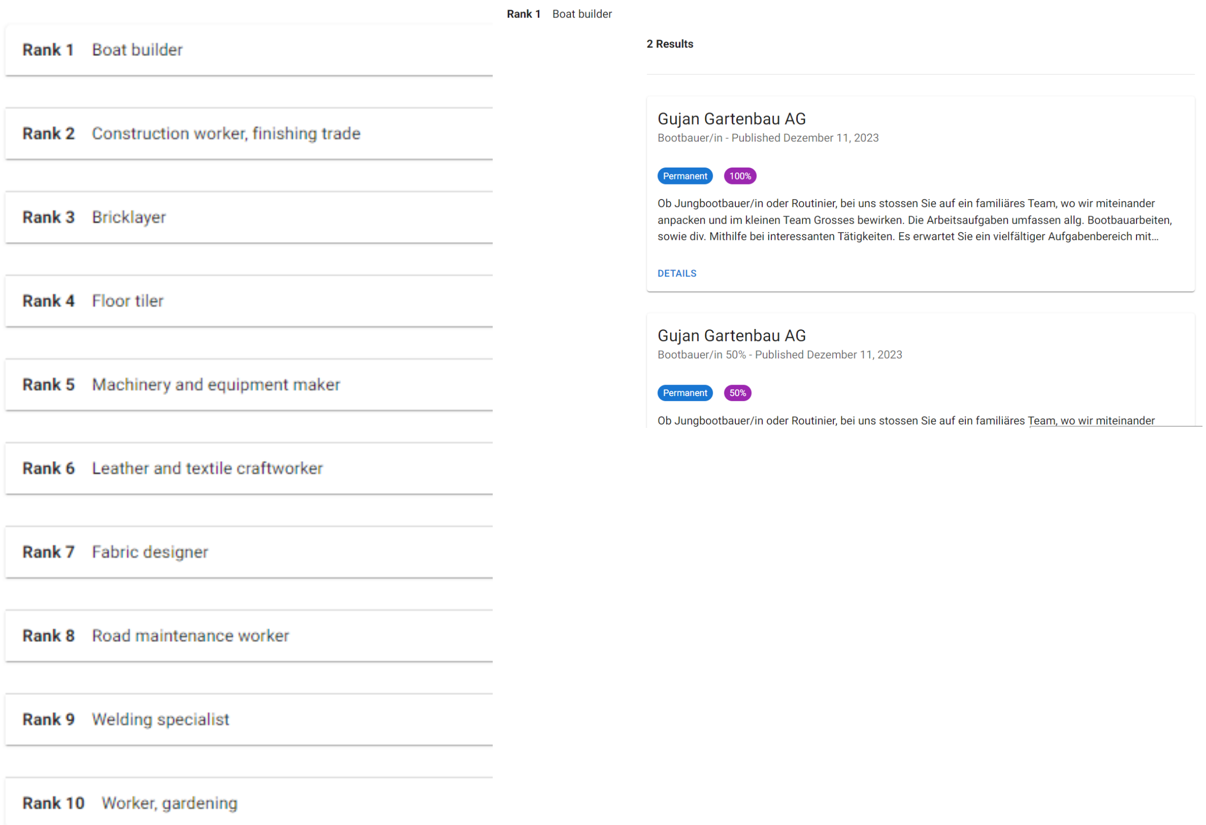
[6]We restrict our analysis to the two O*NET major domains that are worker-oriented (as opposed to job-oriented), namely *Worker Characteristics* and *Worker Requirements*. Within these major domains are the following nine domains: *Abilities, General Occupational Interests, Basic Occupational Interests, Work Values, Work Styles, Basic Skills, Cross-Functional Skills, Knowledge, Education.* To avoid double counting, we exclude the twelve selected descriptors from their original domain so that they only appear in s. For more information about the O*NET content model visit `www.onetcenter.org/content.html`.

[7]For clarity, $d^s(o_i, o) = \sum_{j \in s} \sqrt{(x_j^{o_i} - x_j^o)^2}$, where x_j^o is the O*NET score of descriptor j in occupation o and s is the set of the twelve selected descriptors.

[8]For clarity, $d^s(a_i, o) = \sum_{j \in s} \sqrt{(a_j^i - x_j^o)^2}$, where a_j^i is the score obtained by jobseeker i on descriptor j in the baseline assessment and x_j^o is the O*NET score of descriptor j in occupation o. s is the set of the twelve selected descriptors.

Figure 2: Interventions: occupation recommendations

(a) Ten recommendations (b) Vacancies for first ranked occupation



Note: This figure shows the job search page of the J4U platform. When entering an occupation in the search field (see Figure 1, Panel (b)) the participant sees ten ranked occupations as shown in Panel (a). The ranking is constructed using the proximity indicator $d^E(i,o)$ (equation 1) for the experience-based treatment and $d^P(i,o)$ (equation 2) for the profile-based treatment. When clicking on one of the boxes, all available vacancies are displayed as shown in Panel (b).

that has never been implemented before.

The profile-based recommendations are more likely to be different from the jobseeker's previous occupation compared to the experience-based recommendations. For example, if a worker was employed in an occupation that did not fit perfectly her skill profile (and perhaps lost the job because of such a mismatch), the experience-based treatment tends to suggest occupations in which the jobseeker would still be mismatched. Instead, the profile-based treatment proposes occupations in which the jobseeker would be better matched. Of course, changing occupation involves the loss of some occupation-specific human capital and the experience-based treatment better capitalises on the jobseeker's accumulated human capital.

Figure 2 shows how the platforms presents the occupation and vacancy recommendations. When clicking on the search button (see Figure 1, Panel (b)), the platform displays occupations ranked by proximity, as in Panel (a) of Figure 2. Only the first ten closest occupations are shown. The difference between the experience- and the profile-based treatments is the definition of proximity that is adopted. The experience-based treatment uses $d^E(i, o)$ (equation 1) and the profile-based treatment uses $d^P(i, o)$ (equation 2). By clicking on the name of an occupation, the platform displays all the available vacancies in that occupation, as in Panel (b) of Figure 2.

2.2 Recruitment and random assignment of participants

To recruit participants, we collaborated with the Public Employment Service (PES) in the Swiss canton of Zurich. Zurich is located in the German speaking part of Switzerland. It is the largest canton in the country and it is characterised by a tight labour market with an unemployment rate of 3.4% in 2023 (Q1). It is also a very international and multicultural region with approximately one-third of foreign residents and over 12% of residents whose main language is English, which is why we decided to create a full English version of the J4U platform.

To participate in our study, jobseekers needed to satisfy several eligibility criteria. First, they had to be officially registered with the public employment office, have at least 5 months of residual eligibility for unemployment benefit. In addition, they had to be at least 18 years of age, with at least an upper-secondary degree and sufficient knowledge of German or English (i.e. at least B1 level, assessed by the PES).

During the recruitment phase, which lasted between September 2022 and June 2023, eligible jobseekers were contacted by email and also received information flyers from their case workers during their regular job counselling meetings. The flyers and the email invitations contained a QR code with a link to the online registration form. Jobseekers who completed the registration received a second email with instructions to create an account on the J4U platform. Creating an account required completing the baseline questionnaire with the assessment producing the individual scores of the twelve selected O*NET descriptors. Only the jobseekers who completed the baseline questionnaire including the assessment were eventually enrolled in the study. All participants were presented with an overview of their skill profiles obtained from the assessment and they also received instructions about the functioning of the platform corresponding to their treatment. The random assignment to treatment and control groups happened, with equal probabilities and without stratification, at completion of the registration procedure on the J4U platform.[9] Participants were

[9] There was also a third treatment arm that offered cognitive and mindfulness training online. The impact of this intervention will be discussed in a separate paper.

not informed about the treatment they were assigned to and could access the treatment on the J4U platform only after having completed the baseline questionnaire including the assessment exercises.

To facilitate follow-up, we grouped participants into 36 enrolment cohorts based on the dates when they completed the baseline questionnaires. All those who completed the questionnaire within a span of one week were in the same cohorts. During the following 20 weeks, each cohort received weekly reminders to use the J4U platform and short surveys about their job search activities and outcomes. During weeks 9-10 and weeks 19-20, participants could also redo the assessment exercise to update their skill profile on the J4U platform.[10] All activities were incentivised via a lottery that could generate a total revenue of maximum CHF 2,000.[11]

3 Data and descriptive statistics

In this section, we describe the data sources that we use for our analysis and present some descriptive statistics.

3.1 Data

We start creating the sample of jobseekers for our analysis from the pool of those who were eligible for our study and completed their registration on the J4U platform. For these participants we have data from their completed baseline questionnaires, which include some basic demographics and labour market history, and their assessment exercises, from which we derive their skill profiles, i.e. their individual scores on the twelve selected O*NET descriptors.

Thanks to our own specifically developed job search platform, we also have detailed information about the activities carried out by the participants on J4U. We know the timestamp of each login and each click on any feature of the platform, such as clicks on the search button, the searched occupations and restrictions on contract type and location of the vacancies. Of course, jobseekers presumably use a multitude of job search tools, both online

[10] Occupation suggestions were based on the new and updated skill profile after week 10.

[11] Completing the baseline questionnaires and the profile updates yielded each 20 lottery tickets. Completing the job search survey yielded each 5 tickets. Using the J4U platform for job search yielded max 3 tickets per day. The more lottery tickets, the higher the chances to win the lottery. We draw a first lottery of CHF 500 when all participants passed study week 10. We draw the second lottery of CHF 1,500 when all participants passed study week 20.

and off-line, and J4U is just one of them. We have no information about the job search activities that the study participants carried out outside of the J4U platform.

We linked our own data with administrative sources. From the Swiss Federal Statistical Office we obtain the records of our participants from the most recent census (STATPOP), allowing us to double check the information about age, gender, marital status and nationality from the baseline survey and also enrich our set of socio-demographic variables. From the State Secretary of Economic Affairs (SECO) we additionally received the complete PES files of our participants. This is our main source of data about labour market outcomes. For every jobseeker we know whether they found a job, the date of start and the occupation of the new job. We also know how long they had been unemployed at the time of registration on the J4U platform, if they received unemployment benefits, when and for how long. Finally, the data also include information derived from the preliminary interview that jobseekers undergo when they register with PES. On this occasion, they detail their previous job experience and also indicate the occupations that they would like to target in their job search.

3.2 Descriptive statistics on recommendations and job search

Our final sample consists of a total of 1,264 participants, corresponding to approximately 14.2% of the total population of jobseekers who were invited. Table 1 shows the descriptive statistics and balance checks of some selected variables measured at baseline. We have 465 jobseekers in the control group, 411 in the experience-based treatment and 388 in the profile-based treatment. The average age of the participants in our study is around 45 years, approximately 44% are women and 44% are married. About 40% are Swiss citizens and, at the time of enrolment they had already been unemployed on average for 6.5 months. For none of these variables, the means of the treatment groups are significantly different from the control group.

Figure 3 shows the comparison across treatment groups of two additional variables that are important for our analysis. The first is the self-reported experience in the job preceding unemployment, which is displayed in Panel (a). Participants are asked to report this variable in four categories: no experience, less than one year, one to three years and four years or more.[12] Around 80% of participants report having four or more years of experience in the job preceding unemployment and there does not appear to be any major difference across groups. In Panel (b) we report the distribution of mismatch in the job preceding unemployment. We

[12] A few participants report more than one previous job (141 report two and 9 report 3). In these few cases, we consider the weighted average experience in all previous jobs with higher weights assigned to jobs with longer reported experience (50% for experience of 3+ years, 35% for 1-3 years, 14% for less than one year and 1% for no experience).

Table 1: Summary statistics and balance checks

	Controls [1]	Experience-based [2]	Profile-based [3]	Pairwise diff. [2]-[1]	[3]-[1]
Age	45.333	45.123	45.291	-0.210	-0.042
	(0.473)	(0.521)	(0.523)	(0.702)	(0.704)
1=female	0.441	0.440	0.407	-0.000	-0.034
	(0.023)	(0.025)	(0.025)	(0.034)	(0.034)
1=married	0.441	0.465	0.444	0.024	0.004
	(0.023)	(0.025)	(0.025)	(0.034)	(0.034)
1= Swiss	0.424	0.404	0.402	-0.020	-0.022
	(0.023)	(0.024)	(0.025)	(0.033)	(0.034)
Months of unemployment	6.561	6.796	6.366	0.234	-0.195
	(0.325)	(0.352)	(0.319)	(0.478)	(0.460)
Observations	465	411	388	876	852

Note: This table shows the mean and standard deviation (in brackets) of some selected variables by treatment group. All variables are measured at baseline.

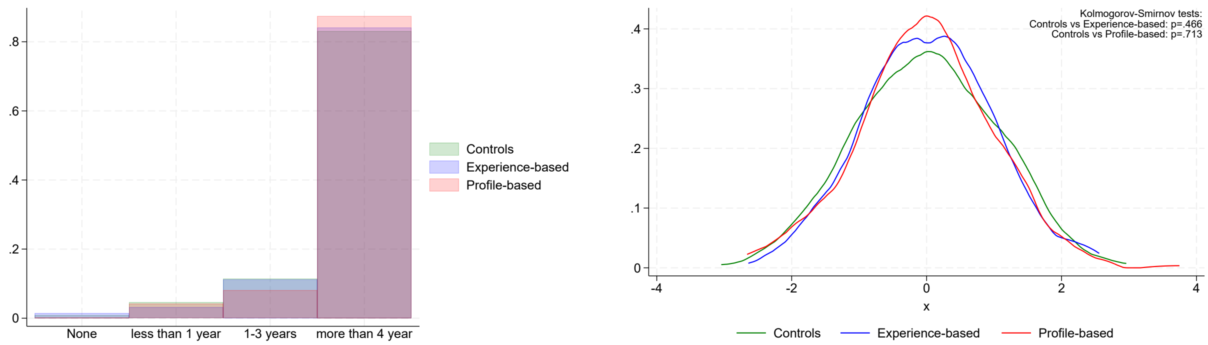
compute this as the Euclidean distance between the jobseeker's profile, as measured by the scores obtained in the baseline assessment exercise on the twelve selected descriptors and the O*NET indicators of the same twelve descriptors corresponding to the occupation of the jobseeker's previous job. Using the terminology of equation 2, this distance is $d^s(a_i, o_i)$. To facilitate the interpretation, we standardise this variable to have mean equal to zero and variance equal to one in the entire sample of participants. Panel (b) of Figure 3 shows that the distribution of mismatch is similar across treatment groups and the Kolmogorv-Smirnov tests fail reject the null of equality between both the experience-based group and the profile-based group with respect to the control group.

4 Results

In this section we present the empirical results of our intervention. We start by showing that the experience- and profile-based treatments provide different recommendations of occupations and that this affects the types of vacancies that jobseekers consult. Next, we look at the outcomes that we pre-registered for the intervention. First, we analyse the rate of job finding and we show that both treatment arms have a positive, although not statistically significant, effect on the overall sample. When exploring heterogeneity along mismatch and previous

Figure 3: Experience and mismatch in the previous job

(a) Experience (b) Mismatch



Note: Panel (a) shows the distribution of self-reported experience in the job preceding unemployment. Panel (b) shows the distribution of mismatch in the job preceding unemployment, which is computed as the Euclidean distance between the jobseeker's profile (measured with the baseline assessment exercise)and the O*NET scores of the twelve selected occupation descriptors (i.e. $d^s(a_i, o_i)$). Panel (b) also reports standard pairwise Kologorov-Smirnov tests for the equality of the distributions between each treatment group and the control group.

experience, we find that, consistent with our intuition, the profile-based treatment improves job finding particularly (and significantly) for jobseekers who used to be mismatched in their previous jobs and had relatively little experience in these jobs. These are the jobseekers who can benefit the most from changing occupation, because they have little occupation-specific human capital to lose and their previous occupations did not match well their skill profiles. For completeness, we also investigate the type of jobs found by those participants who found a job within the study period of eight months since enrolment.

4.1 Recommendations and job search behaviour

When jobseekers register at the public employment office, they indicate the occupations that they would like to target in their search. Figure 4 shows the number of occupations recommended by the J4U platform that also appear in the list of the jobseeker's targets. For this exercise, we consider the occupations that the platform recommends the first time the jobseeker uses it, i.e. the first time he/she clicks on the search button (see Figure 1).

The sets of recommended and target occupations are very different, indicating that our intervention prompts participants to consider jobs and vacancies that they would have presumably not considered otherwise. For about one fourth of participants, none of the listed target occupations corresponds to any of those proposed by J4U and for about 60% the

Figure 4: Recommended and target occupations

Note: The figure shows the number of recommended occupations in each treatment that are also indicated by the jobseekers as target occupations for the their job search at the beginning of their unemployment spell, when their register at the public employment office.

overlap is limited to only one occupation.[13] There is also a substantial difference between the two treatments, with the profile-based arm proposing occupations outside the target set more frequently.

Next, we investigate whether the intervention also affects the types of vacancies that the job seekers look at. We are particularly interested in whether the treated jobseekers look at vacancies that are closer to their skill profiles than their previous jobs. From the platform, we know the exact vacancies on which the users click. As with all the other outcomes, we look at the available data covering the first eight months since enrolment. Over this period, participants click on multiple vacancies: on average about 3 with a median of 2 and the maximum recorded is 34.[14] We group vacancies by occupation and, for each of the clicked occupation o, we compute the Euclidean distance $d^s(a_i, o)$ between the jobseeker's skill profile, as measured by the assessed scores in the twelve selected items that we discussed in Section 2, and the O*NET scores of occupation o in the same twelve items. Then, we compare

[13]Recall that the platform (in both the experience- and profile-based versions) lists a total of ten occupations. There is no restriction to the number of target occupations that jobseekers can indicate when they register at the public employment office and in our data the maximum recorded number is 16.

[14]About half of the participants never clicks on a vacancy. The average number of clicks conditional on clicking at least once is around 13.

this distance with our indicator of mismatch in the occupation preceding unemployment, $d^s(a_i, o_i)$ (see Section 3) and compute the following difference in distances $\Delta_{i,o} = d^s(a_i, o) - d^s(a_i, o_i)$. If the clicked vacancy o is closer to the skill profile of jobseeker i than his/her previous occupation, then $\Delta_{i,o}$ is negative. In reverse, it is positive if the clicked vacancy is farther away. To facilitate the interpretation, we standardize both $d^s(a_i, o)$ and $d^s(a_i, o_i)$ to have mean zero and standard deviation one in the entire sample.

We look at various moments of the distribution of $\Delta_{i,o}$ across all clicked occupations o for each jobseeker i – the minimum, the maximum, the mean and the mode – and we use the following regression model to investigate differences across treatments:

$$\Delta_i^j = \alpha_1^j E_i + \alpha_2^j P_i + \alpha^j X_i + u_i \tag{3}$$

where Δ_i^j is moment j (min, max, mean and mode) of the distribution of $\Delta_{i,o}$, E_i is a dummy indicator which takes value one if jobseeker i is in the experience-based treatment, P_i is a dummy indicator which takes value one if jobseeker i is in the profile-based treatment. The control group is the excluded category. X_i is a set of controls that includes a constant, age, dummies for gender, Swiss nationality, marital status, unemployment duration at the time of study enrolment (in months) and a full set of enrolment cohort dummies.

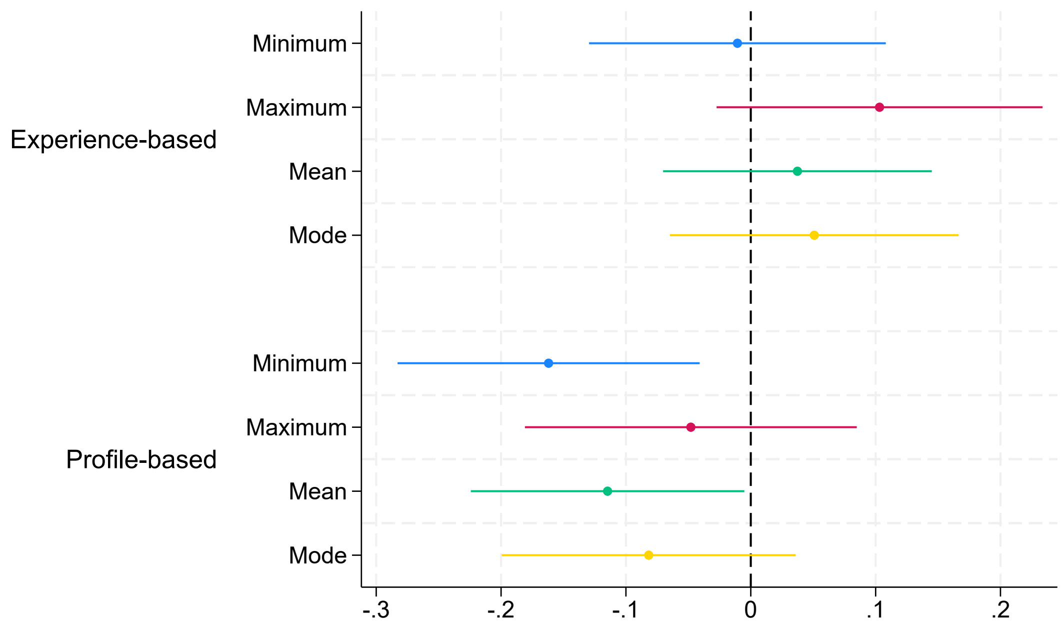
Figure 5 reports the coefficients α_1^j and α_2^j, with their 95% confidence intervals, for all moments j. Overall, we find little evidence that the experience-based treatment affects the types of vacancies clicked by jobseekers compared to the control group. However, the profile-based treatment clearly appears to induce participants to look at vacancies that are closer to their skill profile than their previous jobs. The point estimates are negative for all the moments that we consider and the minimum and the mean are also statistically significant at the conventional level of 95%. The magnitude of these treatment effects are sizeable and in the order of 10-15% of a standard deviation.

4.2 Job finding

We next examine the effect of our intervention on job finding. In Figure 6, panel (a) we report the unconditional cumulative share of participants who find jobs over the eight months following enrolment in our study. Despite the lack of statistical power, participants in both the experience-based and the profile-based treatments find jobs faster than the control group, especially between the second and the fifth months.

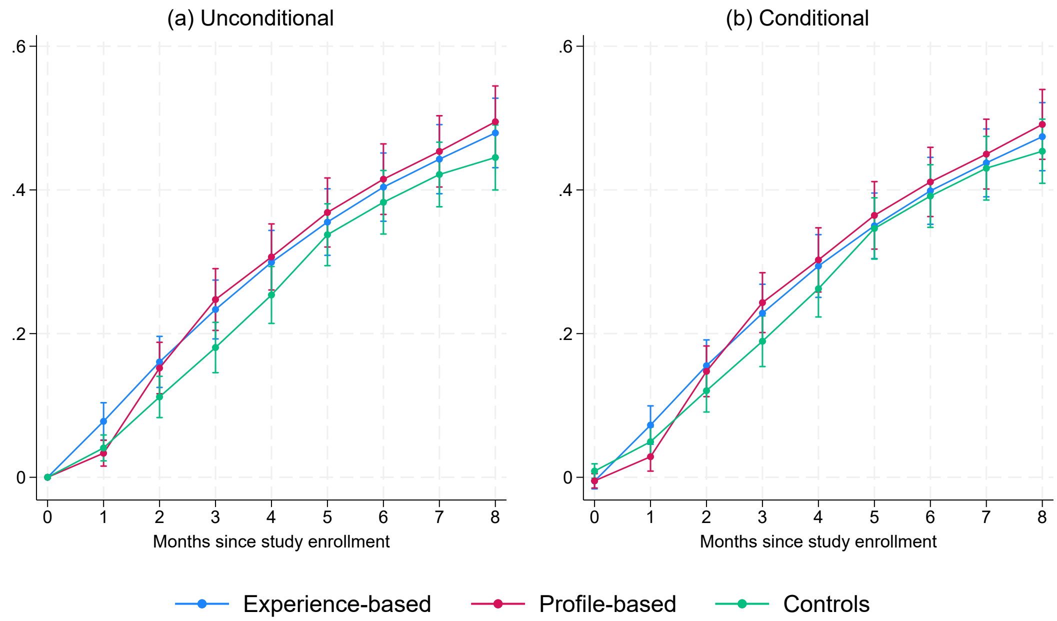
Panel (b) of Figure 6 reproduces the same statistics of panel (a) conditional on our

Figure 5: Mismatch of clicked vacancies



Note: The figure shows the effects of the treatments on the difference in mismatch between clicked vacancies and the previous jobs of the jobseeker. Since participants click on many vacancies during the study period, we consider various moments of the distribution of this difference in mismatch. The dots corresponds to the point estimates of the coefficients α_1^j (upper panel, labelled experience-based) and α_2^j (lower panel, labelled profile-based) from equation 3. The lines represent 95% confidence intervals. A negative coefficient indicates that the clicked vacancies are closer to the participant's skill profile than the previous job. See equation 3 and the related text for details.

Figure 6: Cumulative rates of job finding



Note: The figure shows the cumulative shares of participants who found a job by month since enrolment in the study. Panel (a) shows the unconditional shares and Panel (b) the same statistics conditional on our standard set of controls (age, dummies for gender, Swiss nationality, marital status, unemployment duration at the time of study enrolment and a full set of enrolment cohort dummies. See equation 4 and the related text for details.). The vertical lines represent 95% confidence intervals (standard errors are clustered by individual participant).

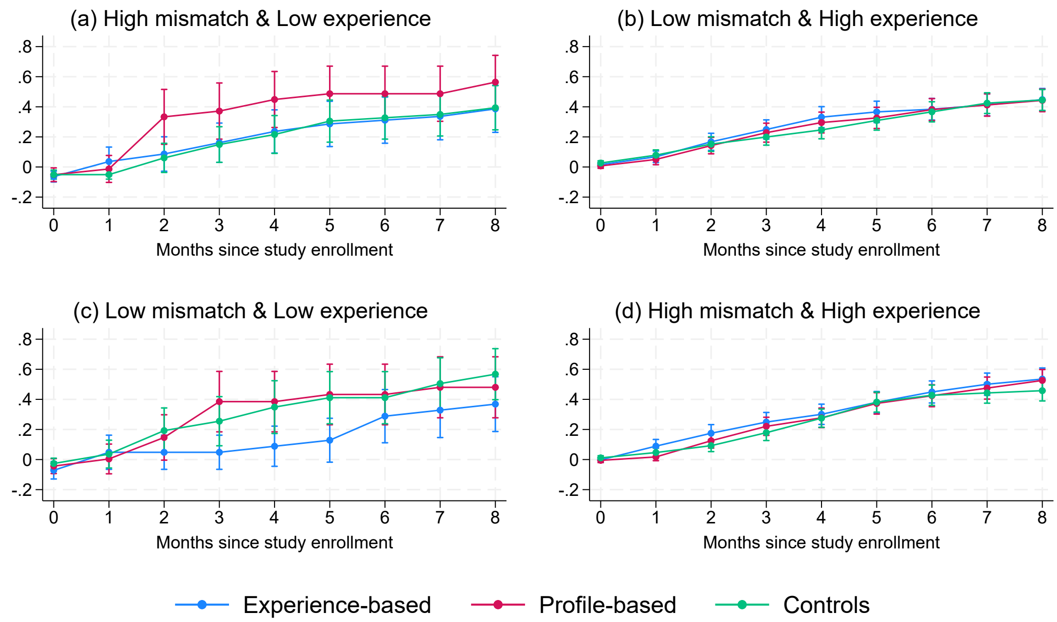
standard set of controls using the following regression specification:

$$y_{im} = \sum_{m=0}^{8} \beta_0^m + \sum_{m=0}^{8} \beta_1^m E_i + \sum_{m=0}^{8} \beta_2^m P_i + \beta X_i + u_{im} \tag{4}$$

where y_{im} is a dummy indicator that takes value 1 if individual i is employed in month m (we count months starting from the time of enrolment in our study) and the explanatory variables are defined as in equation 3. Panel (b) of Figure 6 reports the coefficients β_0^m for the control group, β_1^m for the experience-based group and β_2^m for the profile-based group. Standard errors are clustered by individual participant. Consistent with the random assignment to treatment, the conditional estimates are similar to the unconditional ones.

We expect the profile-based treatment to be particularly useful for jobseekers who were mismatched in their previous jobs and could therefore benefit from searching in different occupations. Moreover, we know from the literature that occupational mobility can be harmful for those with high occupation-specific experience. Hence, in Figure 7 we explore the heterogeneity of treatment effects along these two dimensions. We classify participants into four groups depending on their mismatch in their previous jobs ($d^s(a_i, o_i)$) and their self-reported experience in their previous jobs (these are the variables described in Figure 3).

Figure 7: Cumulative rates of job finding by groups of mismatch and experience



Note: The figure shows the cumulative shares of participants who found a job by month since enrolment in the study, conditional on our standard set of controls (age, dummies for gender, Swiss nationality, marital status, unemployment duration at the time of study enrolment and a full set of enrolment cohort dummies. See equation 5 and the related text for details.). The panels refer to subgroups of participants defined by their mismatch and experience in the previous jobs. High(low) mismatch indicates mismatch above(below) the sample median and high(low) experience indicates 4 years or more in the previous job. All results are conditional on controls: age, dummies for gender, Swiss nationality, marital status, unemployment duration at the time of study enrolment and a full set of enrolment cohort dummies. The vertical lines represent 95% confidence intervals (standard errors are clustered by individual participant). See equation 5 and the related text for details.

We define high mismatch simply as mismatch in the previous job above the sample median and high experience as reported experience in the previous job of four or more years. Eventually, we obtain a distribution of participants across the four groups g with 112 individuals in the group High mismatch&Low experience, 525 in Low mismatch&High experience, 78 in Low mismatch&Low experience and 549 in High mismatch&High experience. The discrete and skewed distribution of self-reported experience (see Figure 3) implies that some of the groups, especially those with low experience, are relatively small compared to the others.

Then, we estimate a model similar to the one in equation 4 but augmented with interactions of the treatment indicators and group dummies:

$$y_{im} = \sum_{m=0}^{8}\sum_{g=1}^{4}\beta_0^{gm}G_i^g + \sum_{m=0}^{8}\sum_{g=1}^{4}\beta_1^{gm}(E_i \times G_i^g) + \sum_{m=0}^{8}\sum_{g=1}^{4}\beta_2^{gm}(P_i \times G_i^g) + \beta X_i + u_{im} \quad (5)$$

where G_i^g are dummies that take value one if participant i belongs to mismach $\times$ experience group g. In Figure 7 we report in each panel the coefficients β_0^{gm}, β_1^{gm} and β_2^{gm} for each group g (across panels) and for each month m (along the horizontal axes). Standard errors are clustered by individual participant.[15]

Despite of the small sample size, Figure 7 clearly shows that the positive effect of the profile-based treatment relative to the control group is concentrated on the participants characterised by high mismatch and low experience in their previous jobs (Panel (a)). This effect is statistically significant at the 95% level in month two and at the 90% level in months three and four. We do not detect meaningful effects of the profile-based treatment in any other group. Somewhat surprisingly, we also find that participants assigned to the experience-based arm have lower job finding rates compared to the control group when they have low mismatch and low experience (Panel (c)). The differences between the experience-based and the control groups are at the margin of statistical significance in months three, four and five.

To summarize the results in Figures 6 and 7 we compute the total number of months spent in unemployment during the study period of eight months since enrolment and we estimate the following equations:

$$m_i = \gamma_1 E_i + \gamma_2 P_i + \gamma X_i + u_i \tag{6}$$

$$m_i = \sum_{g=1}^{4} \gamma_1^g (E_i \times G_i^g) + \sum_{g=1}^{4} \gamma_2^g (P_i \times G_i^g) + \gamma X_i + u_i \tag{7}$$

where m_i is the total number of months spent in unemployment by participants i over the first eight months following study enrolment.[16] All other symbols have the usual meaning. Table 2 shows the estimates of the coefficients γ_1 and γ_2 in the first column (All participants) and the group-specific γ_1^g in the following columns.

Consistent with Figures 6 and 7, the estimates indicate that the treatment effects are generally negative and become sizeable and statistically significant a conventional levels for the profile-based intervention of participants with high mismatch and low experience in their previous jobs. For this particular group, the profile-based treatment results in 1.5 months of unemployment less than the control group. This is a large effect of about one fourth over the

[15] For brevity, we only report estimates produced with the full set of control variables X_i. We do the same for all the remaining estimates in this section. In all cases, the unconditional results are very similar to the conditional ones - which are often more precise - and are available from the authors upon request.

[16] For further precision, m_i is the number of months in non-employment, i.e. individual i could be still registered at the public employment service but either not actively searching and/or not receiving unemployment benefit.

Table 2: Treatment effects on months of unemployment during the study period

	All participants	High mis. Low exp.	Low mis. High exp.	Low mis. Low exp.	High mis. High exp.
Experience-based	-0.164	-0.088	-0.204	1.414*	-0.375
	(0.199)	(0.624)	(0.305)	(0.762)	(0.299)
Profile-based	-0.190	-1.423**	-0.047	-0.012	-0.129
	(0.199)	(0.703)	(0.305)	(0.801)	(0.296)
Mean control group	5.644	5.464	5.829	5.346	5.546
Observations	1,264	1,264	1,264	1,264	1,264

The reported coefficients are the treatment effects of the two treatments (Experience-based and Profile-based) on the number of months spent in unemployment over the first eight months following study enrolment. The first column reports the effects for the entire sample of participants and the following ones for subgroups defined by the participants' mismatch and experience in the previous jobs. High(low) mismatch indicates mismatch above(below) the sample median and high(low) experience indicates more than 3 years in the previous job. All results are conditional on controls: age, dummies for gender, Swiss nationality, marital status, unemployment duration at the time of study enrolment and a full set of enrolment cohort dummies. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See equations 6 and 7 and the related text for details.

average of 5.5 of the control participants. Also consistent with the evidence in Panel (c) of Figure 7, the experience-based treatment increases the number of months of unemployment by 1.4 for participants with low mismatch and low experience in their previous jobs. We return to the interpretation of these results in the discussion section.

4.3 Types of jobs found

We now turn to the analysis of the type of jobs found by the participants in our experiment. From the administrative data we know the ISCO occupation of the job found by those who leave unemployment into employment. Over the follow-up window of eight months since enrolment, 596 out of the 1,264 participants (47.2%) found a new job. This is a highly selected sample and, as we documented in the previous section, the selection process is clearly affected by our intervention. Hence, the evidence discussed here must be interpreted with caution and in the light of the selection process.

We consider four characteristics of the jobs found, the first three of which are part of our pre-registration plan and the last is additional. First, we look at whether the new job is closer to the jobseeker's profile than the previous one. We do so by computing the difference in the Euclidean distances between the skill profile and the previous job and the skill profile and the new job: $\Delta_{i,f} = d^s(a_i, f) - d^s(a_i, o_i)$, where f is the occupation of the new job and the other symbols have the usual meaning. A negative $\Delta_{i,f}$ indicates that the new job is closer to the jobseeker's skill profile than the old job. Second, we consider a dummy indicator for whether the new job is in the same 1-digit occupational group than the old one. Next, we construct another dummy that takes value one if the new job is in the same 1-digit occupational group as any of the target jobs that the jobseeker indicated at the time of registration with the public employment office. Finally, we rank occupations by the median earnings in the occupation (at the 2-digit level) and we create a dummy indicator that takes value one if the job found is in a higher ranked occupation that the previous one. Unfortunately, we do not observe individual wages and this is the best approximation we can produce. For each of these outcomes, we estimate regression models similar to equations 6 and 7:

$$z_i = \delta_1^z E_i + \delta_2^z P_i + \delta^z X_i + u_i \quad (8)$$

$$z_i = \sum_{g=1}^{4} \delta_1^{zg}(E_i \times G_i^{zg}) + \sum_{g=1}^{4} \delta_2^{zg}(P_i \times G_i^{g}) + \delta^{zg} X_i + u_i \quad (9)$$

where z_i is the value of the outcome under investigation for jobseeker i and all the other symbols have the usual meaning. Results are presented in Table 3 in the form of treatment effects using the same format of Table 2, namely δ_1^z and δ_2^z are reported in the first column and δ_1^{zg} and δ_2^{zg} in the following columns by subgroup. Each panel presents the findings of a different outcome.

Results are generally noisy and hard to interpret but we can highlight some overall trends. Neither the experience-based nor the profile-based treatment seem to have an obvious effect on mismatch with the jobs found (panel (a)). Results are imprecisely estimated and likely heavily affected by selection into employment. Both treatments appear to encourage participants to accept jobs that are different from their previous ones (panel (b)). This is particularly true for the profile-based treatment and participants with high mismatch and high experience in their previous jobs. These are the jobseekers who face the sharpest trade-off when considering occupational mobility: if they move to a different occupation they likely lose a lot of occupation-specific human capital but, at the same time, they could benefit a lot from moving because their previous occupations do not fit well their skill profiles. Apparently, for this problematic group the profile-based treatment proposes new jobs that attract their interest. From panel (c) it seems that both treatments also get jobseekers into jobs that are outside the set of those they were considering at the beginning of their unemployment spell. This is particularly true for the experience-based treatment and participants with high mismatch and low experience in their previous jobs. Finally, although the estimates are generally imprecise, there seems to be an overall tendecy for both treatments to improve the quality of jobs found along the monetary dimension (panel (d)).

Table 3: Treatment effects on the characteristics of jobs found

	All participants	High mis. Low exp.	Low mis. High exp.	Low mis. Low exp.	High mis. High exp.
		(a) Δ mismatch			
Experience-based	0.035	0.220	-0.020	-0.234	0.107
	(0.059)	(0.170)	(0.096)	(0.197)	(0.087)
Profile-based	0.046	-0.144	0.043	0.015	0.099
	(0.060)	(0.184)	(0.095)	(0.204)	(0.089)
Mean control group	0.010	-0.141	0.151	0.244	-0.145
		(b) Job found = Previous job			
Experience-based	-0.053	-0.221	0.025	-0.105	-0.077
	(0.052)	(0.149)	(0.084)	(0.170)	(0.078)
Profile-based	-0.058	0.091	0.036	0.000	-0.183**
	(0.052)	(0.151)	(0.085)	(0.172)	(0.078)
Mean control group	0.478	0.417	0.474	0.435	0.512
		(c) Job found = Target job			
Experience-based	-0.132**	-0.294**	-0.101	-0.137	-0.116
	(0.051)	(0.149)	(0.084)	(0.169)	(0.078)
Profile-based	-0.057	-0.006	-0.030	0.042	-0.105
	(0.051)	(0.150)	(0.084)	(0.171)	(0.077)
Mean control group	0.642	0.625	0.671	0.609	0.631
		(d) Job found in higher paying occupation			
Experience-based	0.027	0.013	0.091	0.059	-0.033
	(0.045)	(0.127)	(0.072)	(0.144)	(0.066)
Profile-based	0.020	0.071	-0.038	0.001	0.040
	(0.045)	(0.128)	(0.072)	(0.146)	(0.066)
Mean control group	0.213	0.333	0.132	0.130	0.274
Observations	596	596	596	596	596

The reported coefficients are the treatment effects of the two treatments (experience-based and profile-based) on the outcomes indicated in the title of each panel. The first column reports the effects for the entire sample of participants and the following ones for subgroups defined by the participants' mismatch and experience in the previous jobs. High(low) mismatch indicates mismatch above(below) the sample median and high(low) experience indicates four years or more in the previous job. All results are conditional on controls: age, dummies for gender, Swiss nationality, marital status, unemployment duration at the time of study enrolment and a full set of enrolment cohort dummies. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See equations 8 and 9 and the related text for details.

5 Discussion and interpretation of results

We interpret our interventions as providing jobseekers with information about potential job opportunities that they might not otherwise have considered. The information varies by treatment: the experience-based group receives suggestions for occupations similar to their previous jobs, while the profile-based group receives suggestions for jobs that may be entirely unrelated to their past experience but still align with their skills. The experiment's results indicate that both treatment arms tend to improve job-finding rates (Figure 6) and reduce unemployment duration (Table 2).

Jobseekers who benefit most from the profile-based treatment are those whose pre-unemployment jobs were poorly matched to their skills and who had limited experience in those roles (Panel (a), Figure 7). These workers are more likely to benefit from changing occupations, as their prior mismatch may have contributed to their job loss, consistent with research linking mismatch to a variety of negative job-related outcomes (Leuven and Oosterbeek, 2011). Furthermore, these jobseekers have little occupation-specific human capital, so occupational mobility entails little loss of such capital (Robinson, 2018; Kambourov and Manovskii, 2009). Interestingly, for this group, the experience-based treatment does not significantly improve job-finding rates compared to the control group. This is likely because the experience-based recommendations are similar to their prior jobs, perpetuating the original mismatch.

The second group analyzed in Panel (b) of Figure 7 includes workers with low mismatch and high experience. These individuals are among the least problematic, as their previous jobs aligned well with their skills, and they had accumulated significant experience in those roles. For this group, it makes sense to focus on a straightforward job search strategy: targeting opportunities within their prior occupation. This is the most typical job search strategy and it is the approach likely taken by most control group participants (Krueger *et al.*, 2011; Mueller *et al.*, 2021; Altmann *et al.*, 2023). Consequently, we find no significant difference in job-finding rates between treated and untreated participants in this group. Treated participants in this category appropriately disregard the J4U recommendations.

The groups in the final two panels of Figure 7 face the most challenging trade-off regarding occupational mobility. Panel (c) examines jobseekers with low mismatch and low experience in their previous jobs. These workers have limited incentive to change occupations, as they were already well-matched, but they also have little occupation-specific human capital to lose due to their limited experience. Interestingly, the experience-based treatment reduces job-finding rates for this group, although the effects are only marginally significant. A possible explanation is that the recommended occupations, while similar to their previous jobs, may poorly align with their overall skill profiles, lowering the likelihood of receiving offers. Indeed, job seekers in this group tend to accept jobs that are unlike their target occupations significantly more likely than the control group. In contrast, the profile-based treatment does not appear to harm this group compared to the controls.

The group facing the toughest decisions consists of workers with high mismatch and high experience. For them, the potential benefits and costs of occupational change are both substantial. Neither of our treatment seems to help this group find jobs but, at least, neither seem to harm them either. Further research may be needed to understand how to design interventions that can successfully support the job search activities of these jobseekers.

6 Conclusions

This paper examines two interventions aimed at improving job search through a randomized controlled trial. Both interventions — experience-based and profile-based — provide individualized occupation recommendations to encourage broader job searches. The interventions differ in how they create the recommendations. The experience-based approach relies on information about past work experience, while the profile-based approach uses individual measures of skills and competencies that we assessed during the baseline questionnaire.

The primary innovation of this study is the profile-based treatment, which moves beyond prior work experience to reduce the risk of perpetuating labor market mismatch. Unlike recommender systems based solely on past experience, the profile-based approach leverages directly measured individual skills, addressing mismatch that frequently underlies unemployment. This includes various types of mismatch through the correlation between skills, education and qualifications. For many jobseekers, mismatch in previous jobs may have contributed to their job loss. Our findings demonstrate that the profile-based treatment tends to increase job-finding rates and often outperforms the experience-based approach.

Additionally, we contribute by developing a scalable method to assess individual skill profiles and integrate this data into a purpose-built online job search platform. A key step in this process was selecting effective descriptors to measure a worker's profile (Bächli *et al.*, 2024).

A number of important areas of further research remain. First, future interventions could incorporate individual preferences into recommendation algorithms (Bied *et al.*, 2023). Some jobseekers may be willing to search harder and longer to find jobs that align well not only with their skill profiles but also with their preferences and tastes. Information about the non-pecuniary aspects of jobs, which are crucial for job satisfaction, is often hard to access, and there might be scope to design interventions that enhance its availability and distribution. Second, our platform does not provide information on labour market conditions, but this element could be integrated (Barbanchon *et al.*, 2023). However, online job search platforms already present users with vast amounts of information, raising concerns about jobseekers' ability to process it effectively. It may be worth reconsidering what information is best shared with jobseekers directly and what should be directed to caseworkers at employment offices.

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