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Adapting to Scarcity: The Role of Firms in Occupational Transitions

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Abstract

This paper examines the circumstances under which firms facilitate occupational transitions, complementing prior work that focuses on workers' decisions. We link unemployment insurance records with application diaries and clickstream data from a recruitment platform to causally assess how candidates' occupational histories shape recruiters' hiring decisions. We find that the average candidate from a different occupation faces a 7% lower contact rate than equally qualified candidates who last worked in a recruiter's searched occupation. Using a new measure of skill overlap, we show that 60% of this penalty reflects that movers meet fewer skill requirements than incumbents. Occupational experience and qualifications further reduce the mover penalty, such that certain candidates returning to a prior occupation face no penalty at all. Finally, recruiters adapt to scarcity and contact more movers in tight occupations. Changes in firm behavior account for one-third of the increase in movers' application success in tight versus slack labor markets.

Keywords: occupations; occupational mobility; job requirements overlap; labor demand; labor supply; labor market tightness

JEL Codes: J24, J62, J64

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1 Introduction

Occupational transitions are crucial for workers’ ability to adapt to shocks and structural changes in labor demand. It allows workers to switch from industries and occupations in decline to industries and occupations in demand, thereby fostering structural change in the economy (Acemoglu & Autor, 2011). High occupational mobility can reduce mismatch unemployment (Herz & Van Rens, 2020; Guvenen et al., 2020; Şahin et al., 2014) and dampen the adverse effects of layoffs, automation, and employer concentration on workers’ employment and wages (Bloesch et al., 2022; Carrillo-Tudela & Visschers, 2023; del Rio-Chanona et al., 2021; Gathmann & Schönberg, 2010; Macaluso, 2025; Robinson, 2018; Schubert et al., 2024).

A substantial literature conceptualizes occupational mobility from the perspective of workers.¹ Firms typically do not play an active role; they consider candidates from other occupations if they possess the required skills and credentials. But recent papers suggest that the probability that a position is filled with a ‘mover’—an applicant who last worked in a different occupation than the occupation of the firm’s advertised position—is significantly lower than the probability that it is filled with an otherwise similar incumbent—an applicant who has last worked in the position’s occupation (Behaghel et al., 2024; Azmat et al., 2025). Although this ‘mover penalty’ suggests that firms often prevent occupational switches that job seekers attempt to make, little scientific research exists on the circumstances under which firms prevent or facilitate occupational switches. This is likely because isolating firms’ role imposes steep data demands: Since realized occupational transitions reflect both worker and firm decisions, researchers must observe both who applies to firms’ vacancies and whom firms hire. Causally identifying the mover penalty also requires a research design that accounts for the fact that job seekers are unlikely to decide randomly whether or not to change occupations.

This paper overcomes these empirical challenges with a unique combination of matched admin and online data sets: We link unemployment insurance (UI) register data from Switzerland with two data sources: monthly job search diaries, which record applications to vacancies and associated hiring outcomes; and clickstream data from the recruitment platform ‘Job-Room’ of the Swiss Public Employment Service, where recruiters actively search a database of registered job seekers. These data sets enable monitoring recruiters’ contact decisions when screening profiles of registered job seekers. Both the application

¹For example, Yamaguchi (2012), Autor & Handel (2013), Guvenen et al. (2020), and Lise & Postel-Vinay (2020) conceptualize occupational mobility through the lens of Roy-type choice models. In these models, heterogeneous job seekers sort endogenously into occupations based on the (perceived) fit between their skills and the occupation’s task requirements. Similarly, in the models of Gathmann & Schönberg (2010), Cortes & Gallipoli (2018), and Robinson (2018), workers choose the occupation that offers the highest reward for their skills. Cortes & Gallipoli (2018) also account for the costs of mobility as a function of the task distance between occupation pairs and occupation-specific entry costs (e.g., professional training, licensing, and union membership requirements).

protocols and the recruiter data reveal the composition of the candidate pool of vacancies, including detailed information on candidates’ past occupations and occupational experience. In the case of the recruiter data, we also observe everything recruiters do and see when evaluating candidates: the search terms they enter, the candidates and candidate characteristics displayed to them, and their decisions about whom to contact. This enables us to causally identify the effect of job seekers’ occupational histories on recruiters’ contact decisions using a selection-on-observables research design, similar to other papers using click data from recruitment platforms (e.g., Agrawal et al., 2016; Chan & Wang, 2017; Hangartner et al., 2021; Kopp, 2025).

Our novel data document the importance of firms as gatekeepers of occupational mobility. According to the search diaries, applications from movers—candidates who last worked in a different ISCO four-digit occupation than requested—are 35.7% less likely to result in a hire than applications from incumbents. On the recruitment platform, recruiters have a 27% lower probability of contacting movers compared to incumbents. However, these unconditional mover penalties might reflect that job seekers who attempt to switch occupations lack the necessary qualifications, experience, and skills. More generally, movers may be negatively selected, with low chances of finding employment in any occupation.

We use the recruiter clickstream data to analyze the nature of selection into occupational mobility and to identify the causal effect of candidates’ last occupation on recruiters’ contact rates. Our primary research design compares incumbents and movers with similar qualifications and characteristics by leveraging the fact that the platform shows recruiters all candidates willing to work in the occupation the recruiter searches in. Because most candidates are willing to work in several occupations, the same candidate is sometimes an incumbent and sometimes a mover depending on recruiters’ searched occupation. This enables us to estimate regressions with candidate fixed effects that account for an applicant’s average contact rate across occupations. In addition, the regressions control for search fixed effects and thus compare decisions only among job seekers who are seen by the same recruiter during the same search. The regressions show that movers have a 7% lower contact rate than incumbent job seekers with comparable qualifications, characteristics, and average contact likelihood. The fact that the mover penalty is substantially smaller when including candidate fixed effects than the raw penalty confirms that movers are negatively selected.

Next, we exploit the large number of recruiter decisions on the platform data to systematically characterize the influence of skills, occupational experience, and professional qualifications on the mover penalty. In a first step, we demonstrate that the penalty, in part, reflects the fact that movers are likely to meet fewer of the skill requirements in recruiters’ searched occupation than incumbents. Testing this notion requires measuring the expected skill distance between the position and both an average mover and an av-

erage incumbent, since even an incumbent’s last job might have required skills different from those required for the recruiter’s position. Since existing indices do not quantify skill overlap between positions *within* the same occupation, we construct a novel measure using data on job requirements extracted from the near-universe of online job postings in Switzerland. We randomly select 5,000 vacancy pairs and estimate the proportion of job requirements present in both—a proportion we can compute for ads in different and within the same occupation. We validate this measure by showing that it strongly predicts whether two occupations are classified as “related” according to O*Net. It is also highly predictive of the occupations in which job seekers apply. Using the new measure of skill overlap, we estimate the mover penalty in cases when movers fulfill, on average, the same share of skill requirements as incumbents. In this comparison, the mover penalty falls from 7% to 2.8%, suggesting that a lack of skill overlap is a key reason recruiters are reluctant to contact movers. In addition, we find that incumbents’ contact premium is smaller in less homogeneous occupations with lower within-occupation overlap.

We then estimate contact penalties for different types of movers to determine the relative weight that recruiters place on skill overlap, occupational experience, and qualifications. Consistent with economic intuition and theory, the penalty is largest for job seekers from distant occupations with no prior occupational experience in the recruiters’ searched occupation—a group that accounts for one-third of applications from other occupations in the search diary data. Such candidates face a contact penalty of 16.4%. In contrast, the mover penalty is only 6.25% for the 25% return movers—job seekers with prior work experience in recruiters’ searched occupation. Interestingly, there is a small subgroup of movers who face no contact penalty at all: return movers who hold a degree in the advertised occupation, previously worked several years in the recruiter’s occupation, and likely spent less than a year in a closely related occupation. These results confirm that skill overlap, qualifications, and occupational experience are key determinants of recruiters’ reluctance to hire movers. These results validate the focus on skills and credentials in models of occupational mobility and confirm that firms impose costs on most job seekers willing to move to other occupations.

In the next step, we show that firms’ openness to hire movers varies with the scarcity of incumbent job seekers. Our regressions relate recruiters’ occupational search scope to time-varying measures of labor market tightness in an occupation: the ratio between the universe of job openings and the number of incumbent job seekers in the recruiter’s searched occupation and region. Since there may be cross-sectional correlations between occupational tightness and unobserved firm- and occupation-specific factors affecting recruiters’ hiring decisions, we compare the contact rates of the same recruiter across searches with the same search terms at different points in time. We find that recruiters encountering an increased scarcity of incumbent job seekers are substantially more likely to contact applicants from other occupations. Recruiters’ contact rate for candidates from

a different occupation rises from 15.2% in slack to 20.0% in tight occupations. Recruiters facing scarcity primarily contact more candidates from occupations with above-average skill overlap and from lower-paying occupations. Tightness has only a small effect on the contacts of candidates from distant and better-paying occupations.

Finally, we use the search diary data to take steps towards quantifying the importance of firms' hiring decisions for realized occupational transitions. Quantifying firms' role is challenging because firms' reluctance to hire movers could influence job seekers' application behavior. We could thus underestimate the importance of firms in occupational transitions. We address this challenge by leveraging the fact that month-on-month changes in occupational labor market tightness do not increase the number of movers in the applicant pool of vacancies in our data. This finding suggests that high-frequency changes in tightness in an occupation do not immediately affect movers' decisions to apply to that occupation. Therefore, any positive effect of tightness on movers' hiring rate likely reflects firm rather than applicant behavior. We find that the probability that a hired worker comes from a different occupation rises from less than 50% in slack markets to nearly 80% in very tight markets with few incumbents per vacancy—a difference of 30.4 percentage points. This probability would rise by only 20.3 percentage points in a counterfactual in which firms do not adjust their hiring rates for movers. This back-of-the-envelope calculation suggests that changes in firm behavior account for approximately one-third of the higher application success rate of occupational switchers in tight compared to slack labor markets.

Our paper contributes to several strands of literature. First, it adds to the literature on the determinants and obstacles to occupational mobility, which has primarily focused on job seekers. Recent studies use online job search data to study workers' occupational scope (Banfi et al., 2019; Azar et al., 2022; Altmann et al., 2023; Klaeui, 2025). We extend this literature by characterizing the role of firms' hiring decisions in occupational transitions. We show that the size and determinants of the 'mover penalty' are crucial for understanding when and how workers can switch occupations. In doing so, our work also provides an empirical foundation for targeted job search advice and informs a growing literature testing interventions that offer job seekers tailored occupational recommendations (Belot et al., 2019; Belot, Kircher, & Muller, 2025; Altmann et al., 2022; Dhia et al., 2022; van der Klaauw & Vethaak, 2022; Kircher, 2022; Le Barbanchon, Hensvik, & Rathelot, 2023; Bächli et al., 2025; Harmon et al., 2025).

Our paper also relates to the nascent literature on the impacts of labor market tightness on firms' hiring behavior. Several studies show that firms facing hiring difficulties lower their hiring standards in dimensions such as average candidate acceptance probability, skill requirements, or experience requirements (Modestino et al., 2016, 2020; Lochner et al., 2021; Le Barbanchon, Ronchi, & Sauvagnat, 2023; Ziegler, 2024; Cullen et al., 2025). While prior work has examined how job seekers' occupational search scopes re-

spond to tightness (e.g., Altmann et al., 2023; Ma & Samaniego de la Parra, 2021), we study how occupational tightness affects firms’ willingness to consider applicants from other occupations. Our findings suggest that tightness in an occupation creates opportunities for job seekers to transition into it, particularly from lower-paying occupations with similar skill requirements. In addition, we document that scarcity not only increases recruiters’ search intensity (as in, e.g., Gavazza et al., 2018), but also expands their occupational search breadth, highlighting an additional dimension of how recruiters react to tightness.

The paper most closely related to ours is a contemporaneous paper by Azmat et al. (2025). Azmat et al. (2025) conduct a large-scale correspondence study in six target occupations to analyze how retraining programs affect employer callbacks to applications from movers—fictitious applicants without prior work experience and with different levels of retraining in the target occupations. They find that a long retraining program strongly reduces movers’ call-back penalty relative to otherwise identical incumbents, an effect that is particularly large in tight labor markets. Our study complements Azmat et al. (2025)’s results on retraining programs by examining the application behavior of real job candidates using data and an approach that provides sufficient power to differentiate among various mover profiles. This allows us to demonstrate how occupational experience, professional qualifications, and occupational similarity shape movers’ chances of switching occupations. Moreover, we observe the candidate pool facing a vacancy, which enables us to disentangle and quantify the role of both market sides in actual occupational transitions.

Finally, our work also contributes to the literature on measures of occupational similarity, which are relevant for providing job search advice and for understanding labor market boundaries and labor reallocation. Previous studies use observed occupational transitions (Schubert et al., 2024; del Rio-Chanona et al., 2021; Schmutte, 2014; Belot et al., 2019; Belot, Kircher, & Muller, 2025), task overlap between occupations², surveys among workers (Gathmann & Schönberg, 2010), or vocational education and training curricula (Eggenberger et al., 2018) to measure occupational distance. In contrast, our measure builds on a few existing studies and computes overlap using job requirements extracted from online postings.³ This approach quantifies similarity based on up-to-date

²Most of these studies extract the tasks or skills that are particularly prevalent in an occupation using occupational skill classification systems such as the Dictionary of Occupational Titles DOT (Poletaev & Robinson, 2008; Yamaguchi, 2012; Cortes & Gallipoli, 2018; Robinson, 2018; Bocquet, 2024), its successor O*NET (Alabdulkareem et al., 2018; Belot et al., 2019; Belot, Kircher, & Muller, 2025; Macaluso, 2025; Lyshol, 2022), or the Operational Directory of Trades and Jobs ROME (Goos et al., 2019).

³Leping (2009) measures skill overlap between firms based on job requirements in vacancies from an online job-search platform in Estonia. A key advantage of our measure is that our skill and task classification considers thousands of categories, whereas Leping (2009) considers only three broad skill groups. Other related papers are Bloesch et al. (2022), who construct a measure of within-firm, across-position task differentiation based on US job posting data from Burning Glass Technologies (now Lightcast), and Djumalieva et al. (2018), who apply semi-supervised machine learning techniques to classify occupations

skill requirements and could be used to estimate the similarity of job requirements between regions, industries, or companies. Our results demonstrate substantial variation in job requirement overlap within occupations. We also find that the mover penalty is 2.5 times larger in occupations with high within-occupation skill overlap than in less homogeneous occupations.⁴

This paper is organized as follows. The next section describes the recruiter and application data that we link to unemployment register data. Section 3 presents a simple framework guiding our empirical analyses. Section 4 reports our baseline estimates of the mover penalty. Section 5 introduces our new measure of occupational overlap and shows that overlap and occupational experience are key determinants of the mover penalty. Section 6 shows the effect of tightness on firms’ willingness to consider candidates from other occupations. Section 7 approximates the quantitative significance of firms for occupational transitions. Section 8 concludes.

2 Data

Our empirical analyses are based on two datasets: recruiter search data from an online recruitment platform and job seeker application data.

2.1 Recruiter Click Data From Job-Room

A core innovation of this study is the use of online clickstream data from recruiters to illuminate the circumstances under which they consider occupational switchers. The data stem from the website “Job-Room.ch”, the job and recruitment platform of the Swiss Public Employment Service (PES). Job-Room allows recruiters to look up standardized CVs of potential employees. The click data used in this study were collected between March and December 2017. Hangartner et al. (2021) use the same data to study ethnic and gender discrimination in the Swiss labor market, and Kopp (2025) uses it to show that recruiters penalize male job seekers who express a wish to work part-time.

The candidate profiles visible on the platform stem from job seekers registered at the PES. The platform covers approximately 80% of all registered job seekers in Switzerland. Registration is open to everyone, but mandatory for UI recipients. 61% of registered job seekers are UI recipients. Recruiters are identified by a cookie installed in users’ browsers when they first visit the platform after December 2016. What we term ‘recruiters’ are

based on skill requirements provided in online job ads in the UK. Finally, Dupuy et al. (2024) measure skill overlap and changes over time using job requirements in vacancies advertised in the US. An important difference is that our measure is also well-defined for the overlap between different jobs *within* an occupation.

⁴These results are in line with other empirical evidence, including the high relevance of job titles for job seekers’ application behavior (Marinescu & Wolthoff, 2020) and the predictive power of task variation within occupations for earnings (Autor & Handel, 2013), that job requirements vary within occupations.

thus typically the users of the same browser on the same workstation. The presumably few recruiters who deleted their browser’s cache during the sample period may be counted as several recruiters.

Recruiters who use the platform usually start by entering the occupation for which they are seeking a candidate. Most recruiters also restrict their search to a specific region, either by limiting the results to candidates living in a particular canton or NUTS-II region or to those willing to work in a particular canton or region. After specifying the search filters, recruiters receive a list of up to 100 candidates who exactly match their search criteria. The result list displays the candidates’ gender, canton of residence, and desired work volume (in full-time equivalents), and whether job seekers are “immediately available” or can start to work “by agreement.” The result list also shows the content of an unstructured text field containing “knowledge, abilities, skills” of job seekers. This information is specific to recruiters’ searched occupation. It is only visible if job seekers have filled it out together with their case workers at the PES. If recruiters are interested in a particular candidate, they can select that candidate to view her full profile.

Figure 1 provides a screenshot of the full candidate profile.⁵ Similar to a standard CV, the profile shows detailed information on candidates’ skills and credentials, including their language proficiency, work experience, and educational attainment, as well as personal characteristics such as gender, name, and nationality. At the top of the profile, recruiters can see which occupation a candidate last worked in. Below that, the profile lists all other occupations the job seeker is willing to work in. For each occupation, the profile reveals a candidate’s years of occupational experience in categorical format⁶, a potential professional degree or training in that occupation, and whether that degree is Swiss, foreign but recognized in Switzerland, or foreign and not recognized. In addition, recruiters may again see the text field with a job seeker’s “knowledge, abilities, skills.”

Candidate profiles are shown to recruiters as search results if the recruiter’s searched occupation matches one of the job seeker’s listed occupations. This set of listed occupations indicates where the candidate is willing to work and is defined during the initial meeting between the case worker of the PES and the registered job seeker. The list is rarely updated during the spell, and it is binding: job seekers can be forced to accept a job offer in one of the occupations if they are offered a position. For this reason, job seekers sometimes list fewer occupations than they actually consider during the unemployment spell. Job seekers primarily focus on occupations in which they have work experience.

The primary occupational classification used on Job-Room is an internal, detailed classification developed by the Swiss Ministry of Economics called AVAM. To harmonize the Job-Room data with our other data sources and use an internationally recognized nomenclature, we aggregate job seekers’ occupational data to ISCO-19 four-digit occu-

⁵Appendix Figure A.1 shows a Screenshot of the original, German version of the profile.

⁶The categories are none, less than 1 year, more than 1 year, and more than 3 years.

pations.⁷

If recruiters are interested in a candidate, they can access the candidate’s contact details by clicking on a “Show contact details” button. In 2017, it was not possible to contact and eventually hire candidates on Job-Room without clicking on this button. Hangartner et al. (2021) validate this outcome by showing that each contact click increases the exit rate out of unemployment within 3 months by 2.1%. Below, we use recruiters’ contact clicks as our main dependent variable.

Sample. We impose a small number of sample restrictions on the recruiter dataset. The core restriction is that we retain only searches in which the recruiter specified an occupation, as we otherwise do not know whether a job seeker’s last occupation matches a recruiter’s searched occupation. This removes 62 777 of 469 779 recruiter searches. We also ensure that candidate profiles include information on their last occupation, exclude searches with missing values in the search identifier token, and remove very few searches involving military occupations. Our analysis sample comprises 15 266 233 result list items (candidates matching recruiters’ search terms) from 406 873 recruiter searches.

Descriptive Statistics. Table 1 presents descriptive statistics of the recruiter click-stream data. The top panel presents the characteristics of candidates that appear in recruiters’ searches, differentiating between incumbents (candidates who last worked in recruiters’ searched occupation, column 2) and movers (column 3). The differences between the two groups are relatively small. Incumbents are slightly younger and more experienced in recruiters’ searched occupation. But the movers often have experience in recruiters’ searched occupations, too. Many thus attempt to return to an occupation they previously worked in (“return movers”).

The middle panel focuses on the recruiter side. It shows that recruiters contact 11% of the candidates in the result list and 45.13% of candidates whose profiles they view in full. Notably, contact rates differ by candidates’ occupational background: recruiters contact 12.24% of incumbent job seekers and only 9.64% of movers. On average, the unconditional “mover penalty” on the platform thus amounts to 27%. This average hides substantial heterogeneity across recruiter searches, as shown by Appendix Figure A.2.

The bottom part of Table 1 describes the sample size. In total, we observe 37,665 recruiters who conduct 406 873 searches and see the profiles of 325,545 distinct job seekers. On average, recruiters find 37.5 candidates per search, of which 19.6 have last worked

⁷We convert the AVAM occupation codes into the four-digit ISCO-19 classification using a crosswalk. To construct it, we leverage the fact that unemployment records reveal job seekers’ last occupation according to both the AVAM and ISCO-19 classifications. The crosswalk is thus the ISCO four-digit occupation that is most frequent among all registered job seekers with the same AVAM occupation. For 4995 out of 5801 AVAM occupations, there is a unique mapping from AVAM to ISCO codes. We also aggregate job seekers’ occupational experience to reflect that we work with ISCO four-digit occupations.

Figure 1: Screenshot of the candidate profile on Job-Room

Candidate's Occupations, Qualifications and Experience	
Last occupation held:	Factory Worker
Years of experience in occupation:	more than 1 year
Occupation title:	Auto Mechanic
Qualification for occupation:	foreign, not recognized in Switzerland
Years of experience in occupation:	more than 3 years
Knowledge, Abilities, Skills:	Training in Macedonia
Occupation title:	Construction Laborer
Years of experience in occupation:	more than 1 year
Candidate's Language Skills	
German:	oral: good, written: basic knowledge
Albanian:	oral: very good, written: very good
Additional Candidate Information	
Availability:	by arrangement
Work type:	no information
Gender:	male
Maximum work percentage:	100%
Possible employment duration:	permanent
Highest education level:	Secondary Level II - ISCED 3
Education:	Sec. II - Vocational Education and Training (VET) or equiv. Sec. I - Compulsory School
Desired work region(s):	Major Region 4 (ZH, SH, TG, SG, AI, AR, GL, GR)
Driver's license categories:	B
Further information provided by:	
Address:	RAV Frauenfeld, Thundorferstrasse 37, 8510 Frauenfeld Cantonal Administration
<input type="button" value="Show contact details"/>	
→ <i>Contact button</i>	
<input type="button" value="Back"/> <input type="button" value="Send this candidate as link"/> <input type="button" value="Print view"/> <input type="button" value="⏪"/> <input type="button" value="⏩"/>	

Notes: The figure shows a screenshot of an example candidate profile on Job-Room.ch (own translation).

in their searched occupation. An average job seeker lists 2.3 occupations in which she is willing to work. For 95% of job seekers, one of these occupations is the occupation they last worked in. In terms of occupational coverage, Appendix Table A.1 shows that recruiters disproportionately look for workers in the craft and related trades, particularly construction workers. However, we observe several thousand searches in all major occupations. This allows us to calculate the impact of job seekers' occupational history on contact rates for all major occupations in Switzerland.

2.2 Online Job Search Diaries

The platform data enables us to analyze the causal effect of job seekers' most recent occupation on recruiters' contact rates. However, it also has two drawbacks. First, the data reveal only contact attempts during the initial hiring stage. If the last occupation influences the likelihood of receiving a job offer conditional on being contacted, we may either underestimate or overestimate the importance of the last occupation. Second, it is unclear whether recruiters' behavior on the platform can be generalized to the recruitment behavior of companies in the labor market as a whole. After all, the platform data reveal the behavior of recruiters who actively approach potential employees. Such recruiters may be more open to candidates from other occupations. Therefore, we supplement the Job-Room analyses with analyses of applications from job search diaries of registered unemployed.

Switzerland's unemployment insurance (UI) system requires job seekers who claim UI benefits to document their application activities each month in application protocols. On the protocols, job seekers must provide details of each job they applied for, including the application date, the title of the position, and the name of the company advertising the job. The protocols are an important monitoring tool for the PES to ensure that UI recipients comply with the application obligations. Therefore, the protocols are typically discussed and validated in case worker meetings.⁸

Since 2022, job seekers with a personal account on Job-Room have the option to submit protocols digitally by completing a designated online form (Appendix Figure B.1 provides screenshots). Job seekers using Job-Room to screen job ads can also import the relevant ad information directly into the protocol via a 'Transfer' button. This button is displayed on the website's view page of job postings (see Appendix Figure B.2). When job seekers use the import functionality, the system stores the unique identifier of the job posting, which allows linking an application to the register data of the job opening. Applications documented via the import function account for 28.9% of the total applications

⁸According to Zuchuat et al. (2023), caseworkers randomly check the accuracy of the protocol information by contacting the employers. Since the protocols serve as the basis for potential benefit cuts, which are common in Switzerland, job seekers have a strong incentive to provide correct and complete information (see Zuchuat et al., 2023, for an extended discussion).

Table 1: Descriptive statistics of recruiter click data

	(1) All job seekers	(2) Incumbent job seekers	(3) Job seekers from a different occupation
<i>Job seeker characteristics:</i>			
Number of occupations listed by jobseeker	2.32	—	—
Probability to list last occupation (%)	94.58	—	—
Share female (%)	41.52	42.97	40.59
Average age	39.32	38.71	39.71
<i>Share by highest education (%):</i>			
Tertiary	20.45	20.54	20.38
Upper secondary	51.69	51.50	51.81
Lower secondary	22.06	21.32	22.53
<i>Experience in searched occupation (%):</i>			
More than 3 years	72.16	79.20	64.03
1 to 3 years	16.21	14.31	18.41
Less than 1 year	5.88	4.18	7.84
<i>Experience in last occupation (%):</i>			
More than 3 years	69.73	77.09	61.69
1 to 3 years	19.13	15.33	23.28
Less than 1 year	8.11	4.83	11.68
<i>Recruiter search results:</i>			
Candidates in result list per search	37.52	19.58	17.94
Candidate views per search	9.14	4.95	4.19
Candidate contacts per search	4.13	2.40	1.73
Share contacted (%) (cond. on in result)	11.00	12.24	9.64
Share contacted (%) (cond. on viewed)	45.13	48.40	41.27
<i>Count data:</i>			
Recruiters	37 665	—	—
Searches	406 873	—	—
Result list entries	15 266 233	—	—
Distinct job seekers in result lists	325 545	—	—

Notes: The table reports descriptive statistics of the candidate pool and recruiters' click behavior on Job-Room between March and December 2017. The top panel reports statistics on the job seekers registered with the Swiss PES who are visible on the platform. The middle panel reports averages over recruiter searches. The bottom panel reports aggregate counts.

made by job seekers.⁹

An important feature of the application protocol data is that it can be linked to an indicator showing whether job seekers were hired for the position they applied for.¹⁰ In our sample, we estimate that job seekers have a 1.2% chance of being hired conditional on applying for a job.¹¹

Our analyses below focus on job seekers who use the online form on Job-Room, in combination with the import button on Job-Room job ads, to fill out their monthly application protocols. Although we have application data from the second to the fourth quarter of 2022 only, the sample is quite large: We observe applications by 23 450 job seekers, of which 12 230 job seekers have completed their spell and the re-employment firm is known. For these job seekers, we observe 167 024 applications to 96 611 distinct vacancies. For 775 (0.46%) we cannot assign an applied-to firm using the string-match algorithm and for 2403 (1.44%) the vacancy canton or occupation is missing. Further, for 4546 applications (2.72%), either U or V are zero. In these cases, we cannot compute a tightness measure. We thus show robustness to impute them below. Our final sample thus consists of 159,300 applications. Despite its size, this is not a random sample of job seekers. Appendix Table B.1 shows that job seekers using the Job-Room functionalities are more likely to change occupation upon reemployment compared to the population of job seekers (58% vs. 53%). Apart from that, however, our search diary sample mirrors the characteristics of the population of registered job seekers relatively closely.

3 How Recruiters Shape Occupational Transitions

In this section, we present a simple framework that guides our empirical analyses and defines the core objects of interest of our study. We also aim to clarify what we can learn from the hiring rate of job seekers attempting to change occupation about the importance of firms in occupational mobility.

⁹Since Job-Room contains almost the entire universe of online job openings in Switzerland, job seekers can use this import function for most jobs they have applied for. While these applications are not a random selection of all the applications—they do not include applications made through other channels than via online job postings—Klaeui (2025) shows that the search across occupations and commuting zones in these data correlates strongly with the occupation and the commuting zone of the jobs that job seekers find after leaving unemployment.

¹⁰This is because the UI register contains the name of the new employer for 88% of job seekers who leave unemployment with a job. Therefore, a successful application can be determined by linking the new employer’s name to the names of companies in the protocol data. On a hand-labeled test dataset, our string-matching procedure matches applications to their associated job opening with a balanced accuracy of 91.4%. We discuss the construction of this outcome in greater detail in Appendix A.1.

¹¹A potential concern is that this estimate may underestimate the arrival rate of job offers because we miss certain job matches. Against this background, it is reassuring that the 1.2% job finding rate exceeds the 0.9% job finding rate in Zuchuat et al. (2023), who use manually coded data from Swiss application protocols from 2012 and 2013 combined with direct information from the protocols on whether an application was successful.

Consider the following formula, adapted from Mocanu (2024), which decomposes the share of job seekers hired from a different occupation ($DO = 1$) among all hired workers into the selection decisions of firms and workers:

$$\underbrace{\mathbb{P}(DO=1|Hired = 1)}_{\text{Share of hires from a different occupation}} = \underbrace{\mathbb{P}(Hired=1|DO = 1)}_{\text{Demand for DO}} \times \underbrace{\mathbb{P}(DO = 1)}_{\text{Supply}} \times \underbrace{\frac{1}{\mathbb{P}(Hired = 1)}}_{\text{Overall demand}} \quad (1)$$

Equation (1) shows that the probability that a worker hired by a firm comes from a different occupation, $\mathbb{P}(DO = 1|Hired = 1)$, depends on the probability that recruiters hire a mover conditional on her applying to the job, $\mathbb{P}(Hired=1|DO = 1)$, the share of job applicants that come from a different occupation, $\mathbb{P}(DO = 1)$, and the inverse of the probability that job seekers from any occupation are hired, $1/\mathbb{P}(Hired = 1)$. Subject to the strong assumptions discussed below, one can interpret the first term in (1) as the role of the demand (firm) side in occupational transitions, the second term as the role of the supply side, while the third term captures the competitiveness of the position for job seekers, independent of their occupational background.

Equation (1) suggests that the key quantity governing the role of firms in occupational transitions is the application success rate of job seekers from a different occupation, $\mathbb{P}(Hired = 1|DO = 1)$. Firms play a decisive role when they categorically refuse to hire candidates from an occupation different from the one they seek to fill. In the extreme scenario where $\mathbb{P}(Hired = 1|DO = 1) = 0$, occupational transitions do not occur, regardless of job seekers' application decisions. Conversely, recruiters have no influence on occupational transitions if the hiring probability is independent of a job seeker's occupational background, i.e., if $\mathbb{P}(Hired = 1|DO = 1) = \mathbb{P}(Hired = 1)$. In this case, the probability that a hire comes from a different occupation is determined entirely by workers' application choices.

The application protocol data presented in Section 2.2 enable us to empirically implement the decomposition in (1). The results are presented in Table 2, Panel (a). Of the job seekers who were eventually hired, 63.11% last worked in a different (ISCO four-digit) occupation than advertised in the vacancy (Column 4 of Table 2). However, the share of *applicants* from a different occupation, shown in column 2, amounts to 69.85%. The difference in these two fractions results from the fact that the application success probability, $\mathbb{P}(Hired = 1|DO = x)$, is lower for movers than incumbents (Column 1). While recruiters hire 1.52% of the incumbent applicants, they hire only 1.12% of applicants from other occupations, suggesting that incumbent applications are 35.7% more successful. This premium for incumbency resembles the 27.0% higher contact rate for incumbent candidates in the Job-Room data (see Table 1).

Panel (b) of Table 2 quantifies the importance of the application success channel by

comparing the actual transition probabilities to a counterfactual situation in which firms hire with the same overall hiring rate but movers and incumbents have the same success probability, i.e. $\mathbb{P}(Hired = 1|DO = 1) = \mathbb{P}(Hired = 1|DO = 0)$. Since the composition of hires would depend solely on the supply of job seekers in this counterfactual, 69.85% of the successful candidates would have worked in a different occupation. Taken at face value, these numbers suggest that firms’ reluctance to hire job seekers from other occupations offsets $(41.75 - 29.72pp)/41.75pp = 34\%$ of the occupational changes job seekers attempt. This suggests that the demand side plays an important role in occupational transitions—a point to which we return in Section 7.

Table 2: Decomposition of observed occupational transitions into supply and demand side components

	(1)	(2)	(3)	(4)
	$\mathbb{P}(Hired = 1 DO = x)$	$\mathbb{P}(DO = x)$	$1/\mathbb{P}(Hired = 1)$	$\mathbb{P}(DO=x Hired = 1)$
(a) Observed probabilities				
$DO = 1$	1.12%	69.85%	80.70	63.11%
$DO = 0$	1.52%	30.15%	80.70	36.89%
Difference				26.21pp
(b) Counterfactual probabilities without application success channel				
$DO = 1$	1.24%	69.85%	80.70	69.85%
$DO = 0$	1.24%	30.15%	80.70	30.15%
Difference				39.71pp
Importance of application success channel				$\frac{39.71 - 26.21pp}{39.71pp} = 34\%$

Notes: This table decomposes the share of hires coming from another occupation using the online application protocols from the Swiss Public Employment Service. The sample includes all registered job seekers who have completed their spell with information on their re-employment firm and who transfer applications to the job search diaries from the job platform “Job-Room.”. $DO = 1$ indicates applicants whose last job was in a different occupation than the vacancy; $DO = 0$ indicates applicants whose last job was in the same occupation as the vacancy. Column (1) shows the hiring probability for the two groups of job seekers. Column (2) shows the share of applications from each group. Column (3) is the inverse of the overall hiring probability $(\mathbb{P}(Hired = 1))^{-1}$. Column (4) shows the share of hires from each group, calculated using Bayes’ rule: $\mathbb{P}(DO|Hired = 1) = \mathbb{P}(Hired = 1|DO = 1) \times \mathbb{P}(DO = 1)/\mathbb{P}(Hired = 1)$. Panel A uses the observed hiring probabilities. Panel B presents a counterfactual where hiring probabilities are equalized across both groups at the overall mean (1.24%).

However, Equation (1) separates the roles of demand and supply only under the assumption that job seekers’ and firms’ decisions are independent. There are two main reasons why this assumption is unlikely to hold in reality. First, job seekers likely anticipate recruiters’ hiring preferences. If job seekers expect recruiters not to hire applicants from other occupations, they may refrain from applying to jobs outside their current occupation altogether, leading to $\mathbb{P}(DO = 1) = 0$. Indeed, most theories of occupational mobility assume that workers implicitly consider their chances of being hired when choosing in which occupations to apply. In this case, the above calculation of the application success channel would underestimate the relevance of firms for occupational transitions. Second, recruiters may be reluctant to hire job seekers from other occupations because they may assume that these job seekers are of lower quality. This would be rational if

job seekers attempting to switch occupations were less qualified or negatively selected. In this case, the application success channel would overestimate the role of the demand side, as firm decisions would partly reflect differences in applicant quality.

This discussion delivers two important insights for the empirical analyses. First, understanding why movers have a lower success rate than incumbents requires taking into consideration that applicant qualifications and quality may differ between the two groups. In the following, we use the Job-Room data to study the determinants of the difference between $\mathbb{P}(Hired = 1|DO = 1)$ and $\mathbb{P}(Hired = 1|DO = 0)$. These data allow us to control systematically for job seekers' qualifications and their chances of being hired in any occupation—a direct measure of applicant quality. Second, analyses of movers' application success rates capture the impact of the last occupation on firms' hiring decisions “at the margin,” i.e., for job seekers who, knowing their chances of success, decided to search and apply in a different occupation. If applicants pre-emptively abstain from applying in other occupations because they expect low hiring chances, these analyses will tend to underestimate the overall importance of the firm side for occupational transitions.

4 Firms' Reluctance to Hire Movers

4.1 Empirical Approach

In this section, we estimate the impact of job seekers' last occupation on recruiters' contact attempts on the recruitment platform Job-Room. These analyses require solving several empirical challenges. As discussed in the previous section, a key issue is that job seekers who intend to change occupations may be negatively selected. They may also differ from incumbents in several observed and unobserved ways.

Our data offer several advantages to address this self-selection and other empirical challenges associated with estimating the causal effect of job seekers' last occupation. First, we can leverage the fact that the same job seeker appears in the results lists of recruiters who search in different occupations. We can therefore estimate regression specifications with candidate fixed effects. These fixed effects absorb the average contact rate of a candidate in any occupation, thus controlling for her overall quality. By comparing results with and without candidate fixed effects, we can also test whether those who wish to change occupation are indeed negatively selected. Second, all the information available to recruiters when deciding whether to contact a job seeker is also available to us. We can therefore create control variables that reflect a candidate's qualifications and fit for a given occupation. Third, by adding fixed effects for each recruiter search, we can compare recruiter decisions across candidates who appear in the same search results list. Unless the recruiter uses the same search terms to fill several positions, these fixed effects imply that we compare only job seekers evaluated for the same position. They

also absorb all unobserved recruiter characteristics and the search criteria and eliminate concerns about reverse causality: the fact that the availability of incumbents may affect recruiters’ overall contact rate.

We estimate the effect of job seekers’ last occupation on recruiters’ contact rates on the platform using variants of the following linear probability model:

$$y_{i,s} = \alpha I[o_l(i) \neq o(s)] + \beta X_{i,o(s)} + \gamma_i + \phi_s + \psi_{rank(i,s)} + \varepsilon_{i,s} \quad (2)$$

The unit of observation is a job seeker who appears in a list of search results. The dependent variable, $y_{i,s}$, is the probability that the recruiter clicks on the contact button when screening job seeker i ’s full profile conditional on seeing the candidate in the result list. The key explanatory variable, $I[o_l(i) \neq o(s)]$, is an indicator variable equal to one if candidate i ’s last occupation, $o_l(i)$, does not match the occupation that the recruiter specified on Job-Room in search s , $o(s)$. The parameter α captures the overall average penalty facing a job seeker from a different occupation relative to an otherwise similar job seeker with similar credentials and characteristics who last worked in recruiters’ searched occupation.

The key ingredients in terms of causal identification in (2) are the search fixed effects, ϕ_s , and the candidate fixed effects, γ_i . The search fixed effects imply that we control for all recruiter-specific factors that could influence their search, including recruiters’ average contact rate—the Job-Room equivalent of $\mathbb{P}(Hired = 1)$ —and search-specific factors such as the searched occupation and the labor market situation at the time of the search. The candidate fixed effects, in turn, control for all candidate characteristics that influence contact rates and are constant across searches of recruiters. To account for a potential correlation of job seeker i ’s occupational background and the rank of the job seeker in the result list on Job-Room, we also control for rank fixed effects, $\psi_{rank(i,s)}$, which account flexibly for the absolute rank and relative rank of a job seeker in the list of search results.

The mover penalty α captures the empirical analogue of the difference between $\mathbb{P}(Hired = 1|DO = 1)$ and $\mathbb{P}(Hired = 1|DO = 0)$. Its concrete interpretation hinges on the control variables. Since the specification contains candidate fixed effects, the estimate reflects the mover penalty holding applicants’ average contact rate across all occupations constant. In addition, we sometimes include interactions between recruiters’ searched occupation $o(s)$ and the generic (not occupation-specific) candidate characteristics and credentials of job seeker i . These interactions control for the fact that recruiters in certain occupations may value the same job seeker characteristic—e.g., a certain language skill—more or less, depending on the occupation in which they search. We subsume these “match effects” in the control vector $X_{i,o(s)}$. However, none of the specifications in this section control for the occupation-specific candidate skills and credentials displayed on the Job-Room profiles (see Figure 1), i.e., job seekers’ experience, skills, and educational credentials in

occupation o . The reason is that we view these factors as determinants of the mover penalty. We analyze how occupation-specific skills and qualifications influence the mover penalty in the next section.

4.2 Results

Table 3 shows the results of estimating Equation (2) using OLS. We cluster standard errors at the recruiter level. The regression in Column (1) shows that candidates who last worked in an occupation different from the recruiters' searched occupation face a highly statistically significant contact penalty relative to otherwise similar incumbent job seekers. The mover penalty is of similar magnitude when controlling for the control vector $X_{i,o(s)}$ —3-digit occupation indicators interacted with 64 dummies listed in Appendix Table A.2. These interaction terms account for match effects—potential occupation-specific valuations of job seeker characteristics and credentials that are not occupation-specific.

In terms of magnitude, the mover penalty amounts to -0.77 percentage points in our baseline specification. This represents a 7% effect at the average contact rate of 11%. In absolute value, the mover penalty is equivalent to approximately two-thirds of the premium of having 'Good' or 'Very good' German skills (as opposed to little or no German skills) in the German-speaking part of Switzerland, as Column (4) shows using a specification without candidate fixed effects. The penalty can also be compared with the ethnicity- and gender-based contact penalties that Hangartner et al. (2021) estimate using the same data and a similar approach. The 7% contact gap is comparable to the 6.7% contact penalty faced by women compared to equally qualified men in male-dominated occupations, and the 6.2% penalty for job seekers from Central and Eastern Europe compared to equally qualified Swiss native job seekers.

Although the mover penalty is quantitatively important, it is substantially smaller than the gap in the contact rate between movers and incumbents in the raw Job-Room data (see Table 1). The fact that the conditional penalty is substantially smaller than the raw gap suggests that movers are, on average, negatively selected. Indeed, we can directly test the nature of selection by dropping the candidate fixed effects from our main specification. As the comparison of Columns (1) and (3) of Table 3 shows, the mover penalty is twice as large without the candidate fixed effects that account for candidate quality.

Taking stock, we find that recruiters are reluctant to contact job seekers from a different occupation, in part because job seekers who attempt to switch occupations are negatively selected. Holding job seeker quality constant, the mover penalty amounts to 7%.

Table 3: The contact penalty of job seekers from a different occupation

	(1)	(2)	(3)	(4)	(5)
Last worked in different occupation	-0.0077***	-0.0070***	-0.0151***	-0.0085***	-0.0082***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Good German skills				0.0122***	0.0116***
				(0.0009)	(0.0014)
Age = 30-44					-0.0004
					(0.0007)
Age = 45-59					0.0006
					(0.0006)
Age = 60+					0.0005
					(0.0012)
Candidate FE	X	X			
Recruiter search FE	X	X	X	X	X
Search rank (abs. and rel.) FE	X	X	X	X	X
Searched occ. FE x candidate observables		X			
Controls for candidate observables				X	X
-----	-----	-----	-----	-----	-----
Observations	15,266,233	15,266,233	15,266,233	15,266,233	4,624,254
R2	0.46442	0.46506	0.43919	0.44657	0.48927
N searches	406,873	406,873	406,873	406,873	406,873
N recruiters	37,665	37,665	37,665	37,665	37,665
Baseline prob.	0.1100	0.1100	0.1100	0.1100	0.1100
Sample	All	All	All	All	No text

Notes: This table presents estimates of the contact penalty for movers relative to incumbent job seekers based on Equation (2). The outcome is whether the recruiter clicks on the button to reveal a candidate's contact details. The main regressor is whether the candidate's last occupation differs from the occupation the recruiter entered as a search term. Each observation represents a candidate profile that appeared in the recruiters' result list. See Section 2.1 for a discussion of the estimation sample. Search rank fixed effects are fixed effects for the absolute rank and the relative rank of a job seeker within the list of search results. The 'candidate observables' consist of indicators for all information shown on the candidate profile. These are 64 dummies listed in Appendix Table A.2. In Column (2), we interact these candidate observables with an indicator for the ISCO three-digit occupation searched by the recruiter. 'Good German skills' indicate that the recruiter is searching for a candidate in the German-speaking part of Switzerland and sees a candidate whose German language skills are 'good' or 'very good'. This regression controls for the impact of good German skills for searches in non-German-speaking cantons. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the recruiter level.

4.3 Robustness Checks and Heterogeneity

Robustness These findings withstand various robustness and sensitivity checks. As a first step, Columns (4) and (5) of Table 3 provide three pieces of evidence that validate the selection on observables assumption that is key to our research design. First, Column (4) shows that the results are similar to the main results in Column (1) if we drop the candidate fixed effects, which control for observed and unobserved candidate characteristics, and instead add control variables that account for all candidate information visible to recruiters on the Job-Room profiles. This result supports the selection-on-observables assumption because recruiters’ contact decisions should depend solely on observable candidate characteristics under this assumption.

Second, Column (5) shows that the results remain unchanged when we exclude all job seekers whose unstructured text field contains information on their knowledge, abilities, and skills. This field may contain occupation-specific information about job seekers’ suitability for a particular occupation that is difficult to codify and control for in the regressions.¹² The similarity of the mover penalty in the sample without such information to our baseline estimates suggests that the information in the text field does not materially influence our main estimates.

Third, consistent with selection on observables, Column (5) of Table 3 shows that a job seeker’s age, which we can measure in the UI register but is not shown to recruiters on the candidate profile, has no effect on recruiters’ contact attempts conditional on the candidate observables.¹³ Age would most likely influence their contact rates if recruiters observed it.¹⁴

We present several additional robustness checks in the appendix. First, we evaluate how sensitive the results are to the occupational classification used. Our baseline approach treats a job seeker as a mover if her last occupation differs from the occupation searched by recruiters at the four-digit level of the ISCO classification. Appendix Table E.1, Column (2), shows that the estimated mover penalty remains virtually unchanged when using a match at the three-digit level of the ISCO classification. Second, we examine whether our results are biased because registered recruiters collect additional information about candidates through parallel searches on social media or search engines. Note that this behavior is unlikely to be common because non-registered recruiters do not see a candidate’s name, and because recruiters spend, on average, less than ten seconds viewing

¹²Recruiters see the information in the unstructured field regardless of the searched occupation. This implies that the candidate fixed effects control for the average influence of the text field on contact rates across occupations. However, since the text is occupation-specific, its influence on contact behavior may differ depending on the recruiters’ searched occupation.

¹³We conduct this test on a sample of job seekers without an entry in the “additional skills and competencies” field, as this field sometimes contains experience-related information correlated with age (e.g., “more than twenty years of experience as a construction worker”).

¹⁴Zuchuat et al. (2023) show that there is a strong negative correlation between job seekers’ age and the probability of being invited for a job interview in Switzerland.

job seekers' profiles before making a decision. Nevertheless, we test for this possibility by restricting the sample to profiles viewed for no more than 20 seconds. The estimated mover penalty is shown in Column (3) of Appendix Table E.1. The penalty is slightly smaller in magnitude when this restriction is imposed, but it remains highly statistically significant. Finally, Column (4) of the same table shows that the mover penalty based on contact attempts is slightly smaller than the penalty based on recruiters' clicks on candidates' email hyperlinks on their profile pages. This outcome may be viewed as a more concrete indicator of recruiter interest in a candidate than a click on the contact button.

Heterogeneity. Appendix Figure E.1 presents mover penalties separately for each ISCO two-digit occupation. The figure indicates that it is particularly hard for movers to become a health professional, a personal care worker, a handicraft and printing worker, or an information and communications technician. Appendix Table E.3 presents mover penalties by occupational wage level (Column (2)) and the highest educational attainment of the typical incumbent candidate (Column (3)). The table shows that the mover penalty is smaller in occupations with higher pay and higher educational requirements. Potential explanations for these results are that higher-skilled workers have more transferable skills or that recruiters are particularly open to candidates from other occupations when hiring in higher-skilled occupations. As we discuss in Section 5.1.2, it also reflects that different jobs in higher-paid and higher-skilled occupations tend to be less homogeneous in terms of job requirements than lower-paid and lower-skilled occupations.

5 Skills and the Mover Penalty

The results presented in the previous section show that firms are reluctant to hire candidates who attempt to switch occupations. Models of occupational mobility postulate that the key reason for this reluctance is the movers' lack of occupation-specific skills and qualifications. Therefore, Sections 5.1 and 5.2 test whether skill overlap, occupational experience, and qualifications can explain the mover penalty on Job-Room.

5.1 Skill Overlap

A large literature assumes that occupations produce output through occupation-specific bundling of tasks that in turn require specific skills (Robinson, 2018).¹⁵ This view implies

¹⁵In a seminal paper, Lazear (2009) argues that individual skills may be general, but combinations of skills are often specific to a particular firm. This implies that switching between firms with a similar skill mix is easier than switching between firms with little skill overlap. This framework has been extended to occupations. Several studies suggest that the transferability of skills between occupations is an important factor in explaining occupational transitions and their impact on labor market outcomes such as wages

that the degree of task and skill overlap between occupations is a crucial factor explaining why firms prefer incumbent job seekers: the mover penalty reflects that an average candidate coming from a different occupation fulfills fewer of the job’s skill requirements than an average incumbent.

Examining the role of skill overlap in determining the mover penalty is challenging. It requires measuring the overlap of skills between two jobs in two distinct occupations, then comparing it with the overlap between two jobs within the same occupation. As a consequence, one cannot resort to standard measures of occupational similarity based on the overlap of tasks according to occupational skill classifications (used, e.g., by Gathmann & Schönberg, 2010; Cortes & Gallipoli, 2018; Belot, Kircher, & Muller, 2025; Eggenberger & Backes-Gellner, 2023), as these assume that tasks or skills are homogeneous in jobs in the same occupation. Since transitions across occupations are the outcome of interest, measuring similarity based on observed transitions between occupations, as in del Rio-Chanona et al. (2021) or Schubert et al. (2024), is no viable option either. Building on a few previous studies (Leping, 2009; Djumalieva et al., 2018; Bloesch et al., 2022; Dupuy et al., 2024), we overcome these challenges by constructing a measure of skill overlap based on the overlap in job requirements across job postings. The distinctive feature of our measure is that we quantify overlap between and within occupations on a common scale.

5.1.1 Skill Overlap Between and Within Occupations: A New Index

Approach. Our index measures the similarity of occupations based on the overlap in job requirements in job postings. By “job requirements,” we mean the combination of job tasks, skill requirements, and required educational degrees listed on a job ad. We compute the measure using vacancy data that includes job requirements extracted from more than 1 million job postings. The data cover the near-universe of online job postings in Switzerland between 2016 and 2022 (see Appendix C.1 for details). The data assign each job ad to a four-digit ISCO occupation and come with a highly detailed list of job requirements extracted from the text and the job title of the ads.

There are two reasons we focus on all job requirements rather than just skill requirements. First, we include job tasks because a successful candidate must have the experience and skills to perform them.¹⁶ Second, employers do not always list all skill requirements in a job advertisement. For instance, employers may require a specific educational quali-

or re-employment opportunities (Poletaev & Robinson, 2008; Gathmann & Schönberg, 2010; Yamaguchi, 2012; Cortes & Gallipoli, 2018; Robinson, 2018; Goos et al., 2019; Macaluso, 2025; Bohm et al., 2024, among others).

¹⁶It is also technically challenging to distinguish skill requirements from job tasks in job postings. Job postings often detail the duties and tasks of the open position, as well as the skill requirements for suitable candidates. For example, the word “programming” could be listed as both a skill requirement and a job task in a job posting.

fication because they expect successful candidates to possess the skills of graduates with that degree. Although the data provider annotates certain skill requirements implied by the required qualifications and degrees, we can further reduce concerns about missing these requirements by accounting for the required educational qualifications and diplomas when calculating overlap between jobs.

The computation of the index is straightforward (see Appendix C.2 for further details). First, we randomly select pairs of vacancy postings for each occupation. Then, we calculate the overlap in job requirements for each pair using the Jaccard similarity: the number of job requirements mentioned in both job ads divided by the total number of distinct job requirements in both ads.¹⁷ Second, we repeat step one for 5,000 randomly selected vacancy pairs and then average the Jaccard similarities across the pairs. We compute the similarity for both vacancy pairs across distinct occupations and within the same occupation.

Validation. We validate the measure of job requirements overlap in two ways. First, Appendix Figure C.3 shows that occupation tuples with a job requirements overlap of less than 4% are almost never classified as related according to the O*Net classification of “related” occupations.¹⁸ In contrast, two occupations have a 13% likelihood of being “related” if their overlap exceeds 10%.

Second, Figure 2 shows that the overlap in job requirements is highly predictive of job seekers’ application behavior. Using the search diary data in combination with the UI registry, Panel (a) of the figure shows how often a job seeker applies to jobs in a given occupation during an unemployment spell on the y-axis and the overlap in job requirements between that occupation and the job seeker’s last occupation on the x-axis. The binned scatter plot suggests that job seekers rarely apply to jobs in occupations with less than 5% overlap with their last occupation. In contrast, an average job seeker applies almost four times per unemployment spell to jobs in occupations with 11% or more overlap. Panel (b) shows that we observe this strong positive correlation also if we focus on applications to jobs outside of the job seekers’ last occupation.

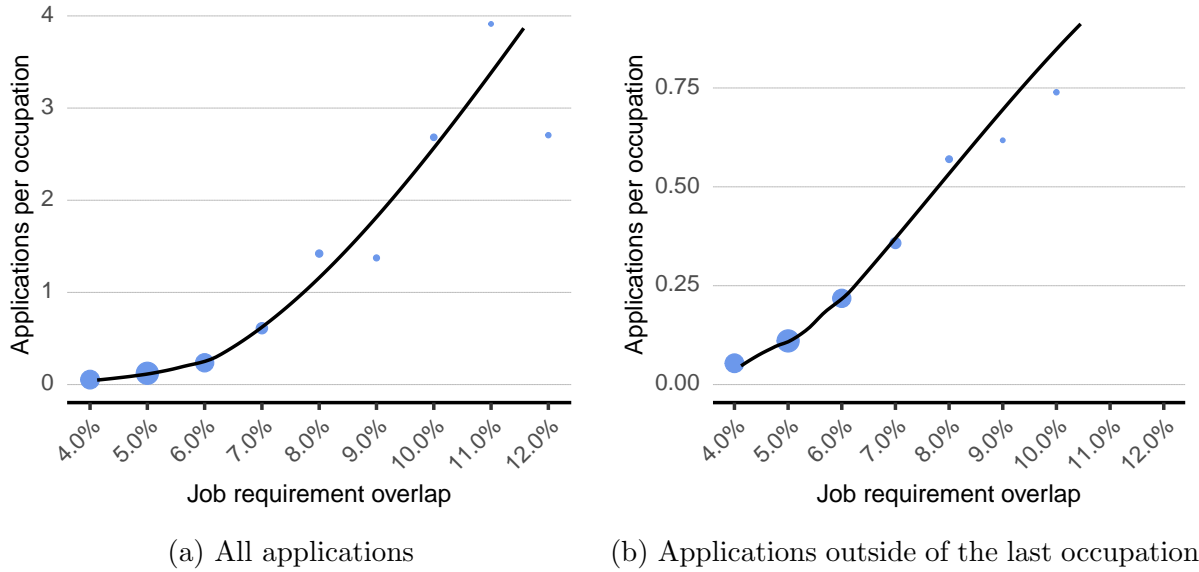
Descriptive Results. Figure 3 shows a matrix of job requirements overlap among the ten occupations with the highest number of registered job seekers in Switzerland. As expected, job requirements tend to overlap more between jobs within occupations than between jobs in distinct occupations. On average, the overlap is 5.5% between two distinct occupations and 9.8% within the same occupation.¹⁹ Nevertheless, vacancies within the

¹⁷Appendix Figure C.1 shows a stylized example for an office clerk and shop sales assistant position.

¹⁸O*Net identifies a fixed number of related occupations for each occupation. Belot et al. (2019); Belot, Kircher, & Muller (2025) use this measure to suggest alternative occupations to unemployed job seekers.

¹⁹Appendix Figure C.2 shows the distribution of overlap between all possible occupation tuples.

Figure 2: Job requirements overlap and applications per occupation



Notes: The figures show binned scatter plots of the number of applications in an occupation against the average overlap in job requirements between the occupation of the vacancy and job seekers' last occupation. Applications per occupation are measured over the job search spell, using the sample described in Section 2.2. The size of the dots is proportional to the number of observations in each bin. The lines represent local linear regressions. The overlap measure is expressed in percentage points and winsorized at the 5th percentile for observations where the last occupation differs from the searched occupation and at the 95th percentile for observations where they are the same. The applications are winsorized at the 95th percentile. Panel (a) is based on a sample with all occupations, and Panel (b) focuses on applications to vacancies in occupations that differ from the job seeker's last occupation. The plot is computed using a 20% random sample of job seekers.

same occupation often have only a few shared job requirements. Furthermore, the overlap within occupations varies substantially. The most homogeneous occupation, with an average overlap of 35.6%, is call center agents and telephone switchboard operators. In contrast, job ads for manufacturing laborers, on average, share only 6.3% of their requirements.

5.1.2 Skill Overlap and the Mover Penalty

Using the new measure of job requirements overlap, we now analyze whether skill distance contributes to explaining why firms disadvantage candidates from other occupations. We investigate this question by extending the specification in (2) with interactions between the indicator for movers, $I[o_l(i) \neq o(s)]$, and indicators of ranges of skill overlap between recruiters' searched and candidates' last occupation. To examine whether skill overlap within occupations also moderates the contact premium for incumbent job seekers, we also add interactions between indicators of overlap and an indicator for incumbent job seekers, $I[o_l(i) = o(s)]$. The omitted reference category is incumbents in a relatively homogeneous occupation with a within-occupation skill overlap of 10.5 to 13.5%.

Figure 3: Job requirements overlap between and within the 10 most common occupations

	Office clerks	Manufacturing labourers	Shop sales assistants	Cleaners	Waiters	Building construction labourers	Kitchen helpers	Freight handlers	Cooks	Stock and transport clerks
Office clerks	7.5	5.1	6.9	6	6.1	4	5.4	4.8	5.4	6.1
Manufacturing labourers	5.1	6.3	6.2	6.1	5.7	6.4	5.5	5.9	5.2	5.6
Shop sales assistants	6.9	6.2	11.1	7.9	8.2	5	6.9	5.8	6.7	6.3
Cleaners	6	6.1	7.9	8.7	8.3	4.4	7	5.6	6.8	5.6
Waiters	6.1	5.7	8.2	8.3	9.3	4.2	6.6	5	7	5.4
Building construction labourers	4	6.4	5	4.4	4.2	10.4	4.6	6.8	4	5.2
Kitchen helpers	5.4	5.5	6.9	7	6.6	4.6	7	5.2	7.2	5.2
Freight handlers	4.8	5.9	5.8	5.6	5	6.8	5.2	7.7	4.5	6.9
Cooks	5.4	5.2	6.7	6.8	7	4	7.2	4.5	11.6	5.1
Stock and transport clerks	6.1	5.6	6.3	5.6	5.4	5.2	5.2	6.9	5.1	9

Notes: This figure shows the average overlap in job requirements between and within the ten occupations with the largest number of job seekers in the Swiss unemployment registry. The numbers indicate the average overlap in job requirements in percent between two job postings from two occupations. The diagonal shows the average overlap in job requirements between two job postings from the same occupation.

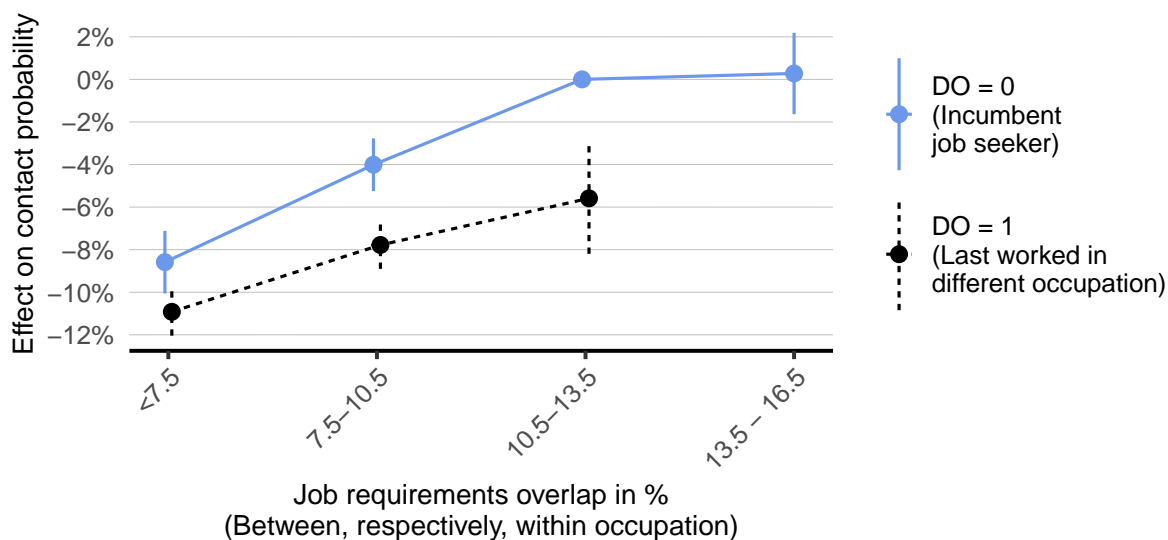
Figure 4 illustrates the results of this regression. The figure provides two important insights. First, the mover penalty, highlighted by the dashed black coefficients, is almost twice as large for movers from an occupation with less than 7.5% job requirements overlap to recruiters' searched occupation compared to movers from an occupation with at least 10.5% overlap. Second, the contact premium of incumbents, captured by the blue coefficients, is substantially smaller in occupations with an overlap of less than 7.5% than in those with an overlap of 10.5–13.5% (the reference category), suggesting that recruiters value incumbents more in occupations with more homogeneous job requirements.

The flipside of this second result is that it is substantially harder for movers to enter a highly homogeneous occupation. Column 4 of Appendix Table E.3 illustrates this. It shows that the mover penalty is 2.5 times larger in target occupations with high within-occupation skill overlap than in those with low skill within-occupation overlap. In addition, Column 5 of that table shows that lower within-occupation overlap goes a long way toward explaining why higher-paid and higher-skilled occupations are easier to enter on the platform: these occupations are less homogeneous on average, reducing the benefit of incumbency.

These results suggest that a lack of skill overlap plays an important role in explaining the contact penalty of job seekers who attempt to switch occupations. To quantify the importance of skill overlap for the mover penalty directly, Column (2) of Appendix Table E.2 flexibly controls for quintiles of skill overlap in the baseline regression. The

specification yields an estimate of the mover penalty for cases in which movers, on average, fulfill the same share of job requirements as incumbents. The mover penalty drops to 0.31 percentage points in this comparison, or by 60% of the baseline penalty of 0.77 percentage points.

Figure 4: Job requirements overlap and the mover penalty



N = 14673984. R2 = 0.47

Notes: This figure shows how job requirements overlap influences the mover penalty on Job-Room based on an extension of the regression model in Equation (2). The outcome is whether the recruiter clicks on the button to reveal a candidate’s contact details. ‘Job requirements overlap’ measures the overlap in job requirements in percent between two average vacancies in two occupations (see Section 5.1.1). The solid blue coefficients show how the contact premium for incumbents varies with job requirement overlap within an occupation. Incumbents in occupations with 10.5%-13.5% overlap are used as the reference category. The dashed black coefficients show the mover penalty at different levels of job requirement overlap. The regression controls for job seeker spell, recruiter search, and (absolute and relative) rank fixed effects. The overlap measure is winsorized at the fifth percentile for observations where the last occupation differs from the searched occupation, and at the 95th percentile for observations where they are the same. Outlier observations with an overlap of more than 16.5% (3.88% of observations) are excluded. Vertical lines represent 95% confidence intervals clustered at the recruiter level.

5.2 Occupational Experience and Qualifications

Although skill overlap is an important determinant of the mover penalty, movers who fulfill a similar proportion of the skill requirements in recruiters’ searched occupation as incumbents still face a 2.8% contact penalty. Can we explain recruiters’ preference for incumbency because recruiters value incumbents’ advantages in occupation-specific qualifications and experience, even when comparing incumbents and movers from jobs with similar levels of skill overlap? To answer this question, we estimate mover penalties separately for different types of movers: candidates coming from differently distant occupations with different levels of experience and qualifications in recruiters’ searched

occupation. The full regression is presented in Appendix Table E.1, Column (7).

Figure 5 shows the resulting group-specific mover penalties derived from this regression. The right side of the figure illustrates the proportions of applicants in each group, both in the Job-Room data (measured as the proportion of candidates in recruiters' search results) and in the application protocol data (measured as the proportion of applicants per vacancy). The Job-Room data shows how occupational switchers are distributed across the different types of movers on the platform. In turn, the protocol data is likely a better approximation of how movers are distributed across categories in the offline labor market. As discussed in Section 2.1, candidates on Job-Room primarily list occupations in which they have work experience. Job seekers' occupational search scope is thus narrower on Job-Room than it is according to the application protocols.

The first coefficient in Figure 5 shows the penalty for movers who have no prior work experience in recruiters' searched occupation and try to find a job in a quite dissimilar occupation: the overlap between their last occupation and the target occupation is at least two percentage points smaller than the within-occupation overlap in the target occupation. In the application protocols, this category accounts for 31.2% of all mover applications. We find that movers in this group face a comparatively large contact penalty of 16.4%.

The second coefficient again illustrates the role of skill overlap: Movers from occupations similar to the target occupation (with less than a 2 percentage-point difference in overlap) face a mover penalty of only 10.9%. Albeit quantitatively meaningful, this contact gap is substantially smaller than the penalties that Azmat et al. (2025) find in their correspondence study for candidates with a similar profile. In their experiment with French job seekers, applicants from a closely related occupation without work experience in recruiters' searched occupation face call-back penalties relative to incumbents of over 60%.

The third coefficient illustrates that the mover penalty is also mediated by the occupational wage level. Interestingly, recruiters, *ceteris paribus*, prefer movers who come from lower-paying occupations. While the magnitude of the wage effect is small, the difference in the mover penalty between candidates from lower- versus higher-paying occupations is statistically significant at the 5 percent level (see columns 5–7 in Table E.1). This result may reflect the expectation that companies will incur higher wage costs or face lower firm tenure when hiring applicants from better-paid occupations. In turn, this suggests that recruiters do not use occupational wage levels as indicators of worker productivity.

The remaining coefficients show the penalties for candidates who have work experience in the recruiters' searched occupation. These movers thus attempt to return to a previous occupation. Prior work experience reduces the mover penalty for job seekers coming from a similar occupation to 6.2% (fifth coefficient), or by 43% compared to an otherwise identical job seeker with no work experience (second coefficient). The penalty drops

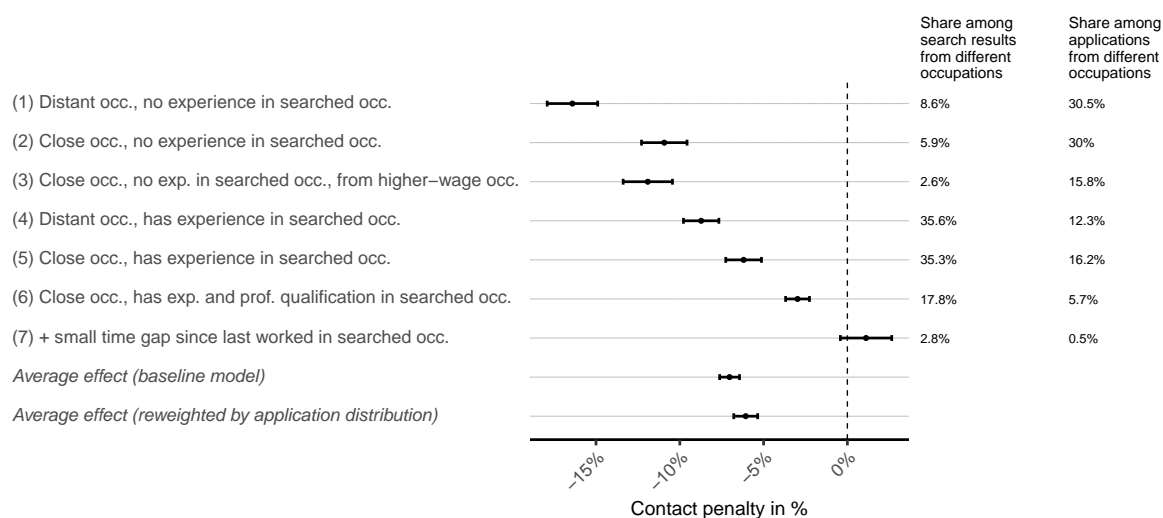
to 3.0% for return movers who also have a professional degree in recruiters' searched occupation (sixth coefficient). Indeed, we find no mover penalty for the small fraction of return movers who have a degree in the searched occupation, come from a similar occupation, and likely only worked in another occupation for a short period of time, as signalled by the fact that the candidate worked in the last occupation for less than one year.

The differences in the candidate shares on the right side of Figure 5 also raise the question of whether the mover penalties derived from Job-Room data accurately reflect the mover penalties in the real labor market. After all, recruiters on Job-Room see a lower proportion of job seekers who consider switching from distant occupations compared to recruiters who receive applications from registered job seekers. Does this imply that the Job-Room data underestimates the average mover penalty in the labor market? The answer is no, as the Job-Room data overrepresents recruiters in occupations that are comparatively difficult for movers to enter. These two effects roughly offset each other. To show this, Figure 5 shows a mover penalty derived from a regression that reweights observations such that their distribution over the types of movers in Figure 5 and two-digit ISCO occupations is equal to the distribution of applications in the search diaries. The reweighted mover penalty is similar in magnitude to our baseline estimate (6.1% versus 7%).

Together, the results in this section suggest that skill overlap, work experience, and occupation-specific qualifications are the primary explanations why recruiters prefer incumbents to otherwise comparable occupational switchers. These results confirm that the mover penalty primarily reflects a perceived lack of skills and credentials, which validates a key assumption of extant models of occupational mobility. The results also shed light on the relative weight that firms place on different indicators of human capital and occupational suitability. For instance, recruiters value work experience and professional degrees above and beyond their implications for the overlap between job seekers' skills and the positions' skill requirements.²⁰ Furthermore, the findings imply that firms impose high moving costs on the large majority of job seekers willing to move to other occupations.

²⁰The fact that recruiters prefer incumbents over and beyond the greater overlap with the position's skill requirements could indicate that recent work experience in the occupation is more beneficial to worker productivity than recent work experience in an occupation with identical skill overlap. It is equally consistent with recruiters having incomplete or biased information about the skill requirements of positions in neighboring occupations. In this case, recruiters may engage in statistical or belief-based discrimination in hiring using applicants' last occupation as a (potentially biased) signal of candidates' true productivity. While it is plausible that recruiters use workers' occupational history, work experience, and educational certificates to infer about job seekers' true productivity (see, e.g. Carranza et al., 2022), models of occupational typically only account for information frictions on the job seeker side (Lise & Postel-Vinay, 2020; Guvenen et al., 2020). An exception of a model with two-sided information frictions is presented by Papageorgiou (2014).

Figure 5: Contact penalties for different types of movers



Notes: This figure shows predicted mover penalties for different subgroups of candidates from other occupations. The outcome is whether the recruiter clicks on the button to reveal a candidate’s contact details. The contact penalties are predictions derived from the regression in Appendix Table E.1, Column (7), holding all controls constant at their mean effects. The distance between two occupations is measured using the overlap in job requirements as described in Section 5.1.1. “Distant occ.” denotes a difference of 2 percentage points (pp) or higher, and “Close occ.” denotes a difference of less than 2 pp. ‘Small gap in time’ denotes a tenure of one year or less in applicants’ last occupation. The last two rows show the estimated average effect from the baseline regression and a reweighted version that aligns the estimation sample with the observed distributions of mover types and (two-digit) vacancy occupations in the search diary data. The horizontal lines represent 95% confidence intervals clustered at the recruiter level. To the right of the figure, we show the proportions of movers in recruiters’ search results on Job-Room and in the online search diary data.

6 Tightness and Firms' Openness to Movers

In this section, we explore whether firms are willing to lower the mover penalty when competition for incumbents increases. Are recruiters more open to considering movers in tight occupations?

6.1 Empirical Approach

We analyze the impact of a scarcity of incumbents on recruiters in two ways. The first approach is to extend the regression model that explains recruiters' contact rates (Equation (2)) with a measure of labor market tightness. More specifically, we use the number of vacancies per unemployed incumbent in the recruiters' occupation and region on day t of search s . Since tightness varies only at the search level, we replace the search fixed effects with recruiter fixed effects and fixed effects for recruiters' search terms—a fixed effect for each combination of occupation and canton or canton group specified by the recruiter. The regressions compare the contact rates of the same recruiter across searches with the same search terms but varying levels of labor market tightness.

One drawback of this first approach is that it requires the recruiter to conduct a search. If tightness affects recruiters' search intensity, this approach could mismeasure its effects on recruiters' occupational search scope. Therefore, we present the results of a complementary approach using data aggregated to the recruiter-month level for each combination of occupation o and location \mathcal{C} . The regression model reads as follows:

$$y_{t,r,\mathcal{C},o} = \beta \log(\text{tightness}_{t,r,\mathcal{C},o}) + \phi_{o,\mathcal{C}} + \delta_t + \theta_r + \varepsilon_{t,r,\mathcal{C},o} \quad (3)$$

where the outcome variable $y_{t,r,\mathcal{C},o}$ represents, for instance, the share of movers that recruiter r contacts in location \mathcal{C} and month t when searching in occupation o . This outcome variable is the empirical equivalent of the left-hand side of the decomposition in Equation (1). We also use variables that represent the terms on the right-hand side of Equation (1), such as the contact rate for candidates from different occupations.

The regression model (Equation (3)) includes calendar month fixed effects δ_t , which control for overall trends in recruiters' contact behavior and seasonal patterns in the search scope common to all recruiters; fixed effects for recruiters' search scope $\phi_{o,\mathcal{C}}$, i.e., fixed effects for each combination of searched occupation and the canton(s) specified by the recruiter; and recruiter fixed effects $\theta_{r(s)}$, which absorb all observed and unobserved recruiter characteristics influencing recruiters' search behavior. As in our first approach, this specification exploits temporal variation in labor market tightness for the same recruiter conducting searches within the same occupation-region cell.

We use platform-external data to construct a daily tightness measure for each occupation-region cell. The numerator is the 30-day rolling average of the stock of online vacancies in

occupation o and region \mathcal{C} around day t according to the x28 job postings data. The data cover the near-universe of online job openings in Switzerland. The denominator is the 30-day rolling average of unemployed individuals registered with the Swiss Public Employment Service who last worked in occupation o and look for a job in region \mathcal{C} around day t . This data stems from the UI register (see Appendix D for further details). Despite the short sample period, we observe substantial variation in the evolution of labor market tightness across occupation-region cells (see Appendix Figure D.1).

Appendix Table E.4, Column (1), validates that this measure of labor market tightness has predictive power on Job-Room. It shows that recruiters searching in tight occupation-region cells see substantially fewer candidates per search than recruiters in slack occupations. Although the candidates on Job-Room are job seekers registered at the Swiss PES, this result is not mechanical. In the denominator of the tightness measure, we only count registered job seekers who last worked in recruiters' searched occupation, not all job seekers willing to work in that occupation. The regression shows that there are fewer job seekers altogether in searches with many vacancies per *incumbent* job seeker.

6.2 Results

Descriptively, there is a clear positive relationship between the vacancy-unemployment ratio in the occupation-region cell of recruiters and their openness to contacting movers (see Appendix Figure E.2). Table 4 analyzes whether this relationship is causal using the first approach discussed in the previous section: a regression that relates the rate at which recruiters contact candidates appearing in the results list to the labor market tightness prevailing in the occupation-region cell on the day of the search. The regression results suggest that labor market tightness increases recruiters' contact rate, the Job-Room equivalent of $\mathbb{P}(Hired = 1)$ in Equation (1). Furthermore, Column (2) shows that tightness increases the contact rate both for incumbent job seekers and, to a slightly larger extent, for movers (the analogues of $\mathbb{P}(Hired = 1 | DO = 0)$ and $\mathbb{P}(Hired = 1 | DO = 1)$, respectively). The estimates imply that movers are twice as likely to be contacted in a very tight occupation compared to a slack occupation (ninety-fifth versus fifth percentile of tightness).

The second approach detailed in the previous section, which is based on data aggregated at the monthly recruiter-occupation-region level and Equation (3), confirms that recruiters facing a scarcity of incumbents become more open to considering movers. The results, presented in Table 5, also show that recruiters adapt to scarcity along several margins: First, tightness increases recruiters' search intensity. Recruiters in tight occupations contact more job seekers overall (Column (1)). Second, tightness increases the probability that a contacted job seeker comes from a different occupation (Column (2))—the Job-Room analogue of the left-hand side of Equation (1)—and decreases the average job

Table 4: Recruiters' contact decisions by labor market tightness in the searched occupation and location

	(1)	(2)
	P(contacted)	P(contacted DO = x)
Last worked in different occupation	-0.0084*** (0.0004)	-0.0080*** (0.0004)
log(Tightness)	0.0160*** (0.0055)	
Last worked in searched occupation x log(Tightness)		0.0152*** (0.0055)
Last worked in different occupation x log(Tightness)		0.0168*** (0.0055)
Recruiter FE	X	X
Searched occ. x canton group FE	X	X
Search rank (abs. and rel.) FE	X	X
Candidate FE	X	X
Calendar month FE	X	X
-----	-----	-----
Observations	15,085,933	15,085,933
R2	0.22127	0.22128
N searches	401,670	401,670
N recruiters	37,288	37,288
Baseline prob.	0.1102	0.1102

Notes: This table investigates how labor market tightness affects recruiters' contact attempts on JobRoom based on an extension of the regression model in Equation (2). Each observation represents a candidate profile that appeared in a recruiter's search results. The outcome is whether the recruiter clicks on the button to reveal a candidate's contact details, $P(\text{contacted}=1)$. $DO = 1$ denotes job seekers who last worked in a different occupation. Tightness is measured as the number of online job openings divided by the number of registered unemployed in the occupation and canton or canton group specified by recruiters in the search filter (see Appendix D for details). The log of the tightness measure is centered around its mean. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the recruiter level.

requirements overlap between the last occupation of contacted job seekers and recruiters' searched occupation (Column (3)). This shows that recruiters in tight occupations contact more job seekers from distant occupations.²¹

Finally, Columns (4)–(6) of Table 5 decompose the positive effect of labor market tightness on the probability that a contacted job seeker is a mover. These regressions suggest positive effects on each component in Equation (1): Tightness increases the share of movers in recruiters' result lists (Column (4)), recruiters' probability of contacting movers (Column (5)), and recruiters' overall contact rate (Column (6)). The results in this table are confirmed if we impute the log tightness measure for the approximately 2% of observations where it is undefined²² and if we restrict the sample to occupation-region cells containing at least 30 job seekers in each month.²³

Figure 6 illustrates the implications of the regressions for recruiters' contact behavior in tight and slack labor occupations and analyzes which movers benefit most from recruiters' increased openness. The top of Panel a) shows that 35.7% of the contacted job seekers are predicted to be incumbents in a slack occupation-region (10th percentile of the tightness measure). In a tight occupation-region (90th percentile), this percentage is 51.5%. The lower part of Panel (a) shows that recruiters facing a scarcity of incumbents mainly contact a greater proportion of movers from occupations with above-median skill overlap. There is no statistically significant effect on movers from more distant occupations. Indeed, recruiters have a low probability of contacting job seekers from distant occupations even in tight occupations. Further analyses presented in Appendix Figure E.3 reveal that the effects of tightness also depend on the wage level in movers' last occupation. Recruiters in tight occupations are substantially more likely than recruiters in slack occupations to contact movers from lower-paying occupations. Tightness has no effect on the share of contacted job seekers from higher-paying occupations.

Figure 6, Panel (b), illustrates the effect of labor market tightness on the contact rate of recruiters, $P(\text{contact} | DO = x)$. A key finding is that movers' contact rate increases from 11.2% in slack markets to 16.7% in tight markets. This increase is driven by a higher contact rate for job seekers from neighboring occupations, rising from 10.5% to 17.5%. In contrast, there is only a small, statistically insignificant effect of tightness on the contact rate of job seekers from occupations with below-median similarity.

²¹The regression also addresses concerns that the results in Column (2) could be sensitive to the occupational nomenclature used. In the regression, we assign the within-occupation overlap to contacted incumbents. The outcome variable in the specification thus measures the distance between contacted candidates' last occupations and the recruiters' searched occupation on a common scale.

²²Tightness is zero in 26,185 out of 1,338,950 recruiter search criteria-month combinations (1.95%). In 153 of these cases, the denominator—the number of unemployed job seekers in the corresponding occupation-canton group—is missing. In the remaining 26,134 cases, no vacancies are recorded in the x28 vacancy dataset for that occupation-canton group in the given month. In the robustness check in Table E.5 we impute a value of 1 for those missing values.

²³This sample is less sensitive to the potential mismeasurement of changes in tightness in very small cells. The results are presented in Appendix Table E.6.

Overall, the estimations suggest that when an occupation is tight, recruiters are less selective about a job seeker’s most recent occupation. Therefore, a tight labor market provides job seekers with opportunities to transition into an occupation. These opportunities are particularly large for job seekers who attempt to transition from a lower-paying, neighboring occupation.

Table 5: The effect of occupational tightness on recruiters’ search behavior

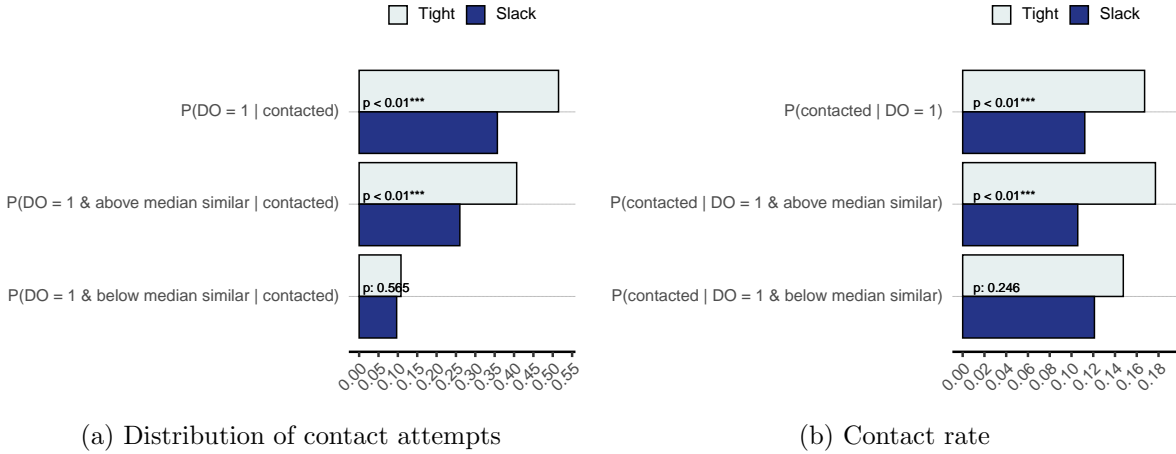
	(1)	(2)	(3)	(4)	(5)	(6)
	N contacts	P(DO=1 contact)	E[overlap contact]	P(DO=1)	P(contact DO=1)	P(contact)
log(Tightness)	0.6301*** (0.0944)	0.0381*** (0.0081)	-0.2972*** (0.0455)	0.0382*** (0.0046)	0.0148** (0.0059)	0.0171*** (0.0060)
Calendar month FE	X	X	X	X	X	X
Occ. x canton scope FE	X	X	X	X	X	X
Recruiter FE	X	X	X	X	X	X
Family	Poisson	OLS	OLS	OLS	OLS	OLS
Observations	1,312,747	112,962	112,962	161,225	153,501	161,225
Mean of dependent var.	1.25386	0.42541	9.30507	0.48612	0.17849	0.20551
Number of recruiters	37,449	23,411	23,411	37,260	36,620	37,260
Pseudo R2 / R2	0.3264	0.4622	0.7501	0.5337	0.4873	0.5131

Notes: This table shows regression estimates of the impact of tightness on recruiters’ search behavior, based on Equation (3) and the sample described in Section 2.1. The estimates are from Poisson (Column 1) and OLS regressions (Columns 2–6) where each observation represents a recruiter-month-occupation-location combination (“a cell”). Only combinations with at least one search over the whole sample period are considered. The outcome variables are the following: Column (1): the total number of contacted candidates per cell; (2) the share of movers among the contacted candidates, restricting the sample to cells with at least one contact; (3) the average job requirements overlap between recruiters’ searched occupation and the last occupation of the contacted candidates, using the sample from Column (2); (4) the probability that a candidate in the results list comes from a different occupation, focusing on cells with at least one search result; (5) the contact probability for movers, using cells with at least one result in a different occupation; and (6) the overall contact probability for all candidates, using all cells with at least one search result. Occupational tightness is measured at the monthly level within the searched occupation-location cell, computed as the average daily vacancy stock divided by the average daily incumbent job seeker stock. See Appendix D for details. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the recruiter level.

7 The Role of Firms over the Business Cycle

The previous analyses have shown that companies are often reluctant to hire job seekers attempting to change occupations, especially when there is an abundant supply of incumbents. What remains less clear from our analyses is the quantitative significance of firms in occupational transitions overall. Having analyzed the determinants of firms’ demand for movers, $P(Hired=1|DO = 1)$, this section thus provides a back-of-the-envelope calculation of how much this term contributes to explaining occupational transitions, $P(DO=1|Hired=1)$. The quantification is based on the following thought experiment: How would the proportion of movers hired change between a tight and a slack labor mar-

Figure 6: Recruiters’ contact attempts in tight and slack occupations



Notes: The figure illustrates the effect of labor market tightness on recruiters’ contact decisions on Job-Room, predicted using estimates from Equation (3). Panel (a) shows the occupational composition of contacted job seekers. Panel (b) shows the predicted contact rate for movers ($DO = 1$). We differentiate between movers from occupations with above-median and below-median job requirements overlap to recruiters’ searched occupation. The median is computed among the search results of recruiters and is allowed to vary by searched occupation. The underlying regressions are shown in Appendix Table E.7. The predictions are obtained by holding all control variables constant at their mean effects. “Tight” (“Slack”) refers to predictions at the 90th (10th) percentile of the distribution of labor market tightness. The figure reports the p-values for the coefficient on $\log(Tightness)$, with standard errors clustered at the recruiter level.

ket if firms did *not* adapt the probability of hiring movers, i.e., if $P(Hired=1|DO = 1)$ stayed constant when tightness changes?

As discussed in Section 3, a significant concern in such a quantification exercise is that firms’ reluctance to hire movers could influence job seekers’ application behavior. This counterfactual approximates the role of firms in occupational transitions under the assumption that applicants from *other occupations* do not respond when an increased scarcity of incumbents leads firms to alter their hiring probabilities for movers. Although this assumption is strong, it is not implausible. Belot, de Koning, et al. (2025) find that job seekers’ targeted occupations do not react to changes in labor market tightness in feasible alternative occupations. Additionally, our quantification exploits high-frequency changes in occupational tightness. Using application data, we demonstrate that the number of applicants from other occupations does not increase in response to month-to-month increases in tightness in an occupation. If increased tightness does not immediately attract more movers, we can attribute the tightness-induced *changes* in the success rate of movers, $P(Hired=1|DO = 1)$, to the firm side. These changes neither reflect job seekers’ anticipation of altered hiring chances nor changes in the quality of movers.

To implement the counterfactual exercise, we use an extended version of Equation (1) that clarifies that the third term in (1) represents an average over the hiring probabilities

of movers and incumbents, weighted by the share of applicants in the two groups:

$$\mathbb{P}(\text{DO} = 1 | \text{Hired} = 1) = \frac{\mathbb{P}(\text{Hired} = 1 | \text{DO} = 1) \times \mathbb{P}(\text{DO} = 1)}{\mathbb{P}(\text{Hired} = 1 | \text{DO} = 1) \times \mathbb{P}(\text{DO} = 1) + \mathbb{P}(\text{Hired} = 1 | \text{DO} = 0) \times (1 - \mathbb{P}(\text{DO} = 1))} \quad (4)$$

Our back-of-the-envelope estimation based on this equality has three steps. First, we estimate how the mover share in the applicant pool, $\mathbb{P}(\text{DO} = 1)$, varies with labor market tightness. Based on the results using the Job-Room data in Table 5, Column (4), we expect that tightness increases this share. Second, we estimate how strongly the hiring rate of movers, $\mathbb{P}(\text{Hired} = 1 | \text{DO} = 1)$, responds to changes in labor market tightness.²⁴ Based on the results in Figure 6, Panel (b), we expect that recruiters in a tight market hire a larger proportion of movers. Third, we compare the effective hiring rate of movers in slack versus tight labor markets—the difference in $\mathbb{P}(\text{DO} = 1 | \text{Hired} = 1)$ —against a counterfactual where the difference in $\mathbb{P}(\text{Hired} = 1 | \text{DO} = 1)$ in slack and tight markets is held constant.

We conduct this analysis both with the job search diary and the recruitment platform data, focusing on the diary data in the main text. To implement steps 1 and 2, we regress the composition of the applicant pool and applicants’ success probabilities on labor market tightness. Our empirical approach resembles the second approach used in Section 6. Tightness represents the ratio of vacancies to incumbent job seekers in recruiters’ searched occupation and is measured at the occupation-canton level within ± 15 days of the vacancy posting date. The regressions control for calendar month and, in our preferred specification, also firm fixed effects. Thus, the estimation exploits both temporal variation and variation in tightness when the same firm fills vacancies in different regions or occupations.²⁵ The regression equation is

$$Y_{j,c,o,t} = \log(\text{tightness})_{t,c,o} + \gamma_{f(j)} + \delta_t + \varepsilon_{jt} \quad (5)$$

for the composition of applications to vacancy j , in canton c and occupation o , where δ_t is a calendar month FE and $\gamma_{f(j)}$ is a FE for the hiring firm.

The results, presented in Columns (1) and (2) of Table 6, suggest that tightness increases the share of movers in the applicant pool. Illustrating these results, Figure 7, Panel (a), shows that the share of movers amounts to approximately 60% in slack occupations (10th percentile of tightness) and more than 75% in tight occupations (90th

²⁴The mover penalty enters the the denominator in Equation (4) as follows

$$\mathbb{P}(\text{Hired} = 1) = \underbrace{[\mathbb{P}(\text{Hired}=1 | \text{DO} = 1) - \mathbb{P}(\text{Hired} = 1 | \text{DO} = 0)]}_{\text{mover penalty}} \times \underbrace{\mathbb{P}(\text{DO} = 1)}_{\text{share of movers}} + \underbrace{\mathbb{P}(\text{Hired} = 1 | \text{DO} = 0)}_{\text{incumbent hiring success}}$$

²⁵This is in contrast to the estimates in the previous section, which relied on temporal variation in tightness only. This adjustment is owed to the short sample period, with most of the application data concentrated in the fourth quarter of 2022. The short sample period implies that estimates based on temporal variation alone are imprecise.

percentile of tightness). Columns (3) and (4) of Table 6 show that the change in the applicant pool reflects a strong reduction in the number of incumbents (Column 3). The number of applicants from other occupations reacts little to tightness. If anything, the number *decreases* with tightness. These results lend support to the assumption that month-on-month changes in the scarcity of incumbents do not immediately attract more applicants from other occupations.

Columns 5 and 6 of Table 6 present applicant-level logit regressions of applicant i 's hiring probability at vacancy j on log tightness, interacted with indicators for whether the applicant is an incumbent or a mover, respectively. Figure 7, Panel (b), illustrates the estimated effects. We observe that the success rate of movers increases from 1.25% in slack occupations to over 1.75% in tight ones. In contrast, the hiring probability of incumbent applicants is quite independent of tightness. Consequently, in tight labor markets, applicants from other occupations have nearly the same chance of being hired as incumbents. These results are robust to several robustness checks.²⁶

Figure 7 uses the regression estimates from Columns 2 and 4 of Table 6 in conjunction with Equation (4) to predict the probability that a hired worker comes from a different occupation at different levels of labor market tightness. This probability increases from less than 50% in slack labor markets to nearly 80% in very tight markets—a difference of 30.4 percentage points. The counterfactual where firms do not adapt the probability of hiring from a different occupation, $\mathbb{P}(Hired = 1 | DO = 1)$, is shown by the dashed line in Figure 7, Panel (c). In this counterfactual, the probability would only increase from 55% at low levels of tightness to 75% at high levels, or by 20.3 percentage points. Thus, the counterfactual suggests that $(30.4 - 20.3pp)/30.4pp = 33.2\%$ of the increase in the hiring probability of movers in tight versus slack occupations is due to the firm side.

We find a slightly smaller contribution of the firm side if we conduct a similar counterfactual exercise using the Job-Room click data. In particular, Appendix Figure E.4 shows that the estimated cyclical sensitivities of contact rates and the candidate pool composition in Table 5 imply that recruiters account for 18% of the positive effect of tightness on the contact probability of movers.

In sum, the two back-of-the-envelope exercises indicate that changes in firm behavior contribute meaningfully to the higher application success rate of occupational switchers in tight compared to slack occupations. Incidentally, the calculated contributions of firms to occupational transitions in both data sets are between the 29% contribution of the application success channel in the simple decomposition in Table 2. Although these calculations are derived under a strong assumption and can thus only approximate the

²⁶First, we address potential issues arising from cells with zero vacancies or unemployed workers by replacing zeros with ones before taking logarithms. Second, we exclude observations from cells with fewer than 30 vacancies to ensure that our tightness measure is based on a sufficiently large sample size and to reduce noise from small-cell variation. The results are presented in Appendix Tables E.9 and E.10 and align closely with the baseline specification.

importance of the firm side for occupational transitions, they suggest that firms play a significant role in shaping workers' ability to change occupations.

Table 6: Tightness, applicant pool composition, and application success probability

	P(DO=1)				P(hire DO = x)	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.:	P(DO=1)	P(DO=1)	N DO=0	N DO=1	P(hire DO = x)	P(hire DO = x)
log(Tightness)	0.1971*** (0.0128)	0.2681*** (0.0160)	-0.2400*** (0.0108)	-0.0226*** (0.0079)		
DO = 1					-0.3073*** (0.0733)	-0.4435*** (0.0823)
DO = 0 x log(tightness)					-0.0615 (0.0412)	-0.0213 (0.0559)
DO = 1 x log(tightness)					0.1101*** (0.0400)	0.1312*** (0.0488)
Calendar month FE	X	X	X	X	X	X
Firm FE		X	X	X		X
Number of vacancies	92,271	92,271	92,271	92,271	92,271	92,271
Observations	92,271	92,271	92,271	92,271	159,300	159,300
Mean of dependent var.	0.69687	0.69687	0.53001	1.19642	0.01249	0.01249

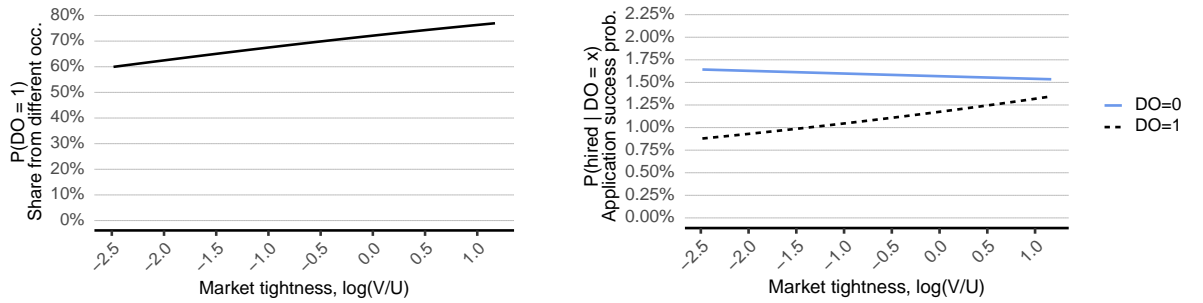
Notes: The table shows the effect of tightness in the occupation-canton cell of the vacancy on the composition of the pool of applicants and applicants' success probability using the search diary data. The regression specification is Equation (5). The estimates in Columns (1) and (2) are from a quasibinomial GLM regression with a logit link. The dependent variable is the share of applicants who last worked in a different occupation. The estimates in Columns (3) and (4) are from a Poisson model. The dependent variable is the number of incumbent applicants ($DO = 0$, Column (3)) and the number of applicants from a different occupation ($DO = 1$, Column (4)). The estimates in Columns (5) and (6) are from logit regressions. The dependent variable is a binary indicator of whether the firm posting the vacancy hired the applicant. The unit of observation is a vacancy posting in Columns (1)–(4) and a vacancy-application combination in Columns (5)–(6). The sample is described in Section 2.2. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

8 Conclusion

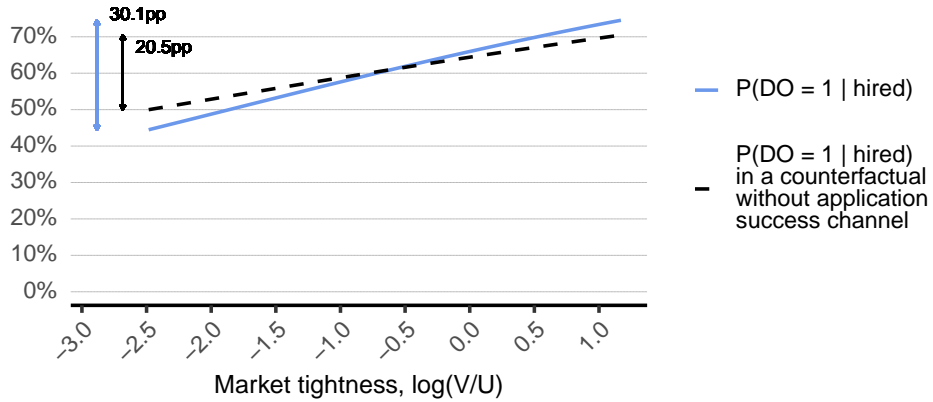
This paper examines the circumstances under which firms consider applications from job seekers who last worked in a different occupation from the one the firm is advertising. We combine two unique sources of data that we can both link with unemployment insurance register data: click data from the recruitment platform of the Swiss Public Employment Service, revealing contact decisions of recruiters screening registered job seekers, and monthly online job search diaries, recording job seekers' applications to vacancies and the associated hiring outcomes. These data allow us to identify the impact of job seekers' occupational histories on firms' hiring decisions. We additionally develop and validate a new measure of occupational similarity based on job requirements overlap between vacancies.

Our analyses yield four main insights regarding the role of firms in occupational tran-

Figure 7: Decomposition of the effect of tightness on occupational transitions



(a) Tightness and applicant composition (b) Tightness and application success probability



(c) Counterfactual exercise

Notes: The figure illustrates the relationship between labor market tightness and different components of Equation (4): a) the predicted share of applicants who last worked in a different occupation ($P(DO = 1)$), b) the application success probability of incumbents ($P(Hired = 1|DO = 0)$, solid blue line) and movers ($P(Hired = 1|DO = 1)$, dashed black line), and c) the predicted share of hires from a different occupation, $P(DO=1|Hired = 1)$ (solid blue line). Panel (c) also shows $P(DO=1|Hired = 1)$ under a counterfactual scenario where the application success rate of movers, $P(Hired = 1|DO = 1)$, is held constant at its average value for each value of labor market tightness (dashed black line). All predictions are calculated based on the estimation results in Columns 2 and 4 of Table 6 and hold the effects of all other variables constant at their mean effects. The x-axis ranges from the 10th to the 90th percentile of labor market tightness.

sitions. First, recruiters prefer incumbents. According to the search diary data, applications from movers are approximately one-third less likely to result in a hire than those from candidates who search within their last occupation. The mover penalty is similarly large in contact attempts on the recruitment platform. Once we hold job seeker quality and qualifications constant, the mover penalty decreases but remains quantitatively significant at 7%. Second, 60% of the mover penalty is attributable to the fact that movers come from positions with lower overlap in job requirements than incumbents. Furthermore, recruiters value prior occupational experience and occupational qualifications—so highly that return movers who have worked in a similar occupation for a short time and have occupational credentials and sufficient experience in the recruiters’ searched occupation face no mover penalty. Third, when there is a scarcity of incumbents in an occupation, recruiters are more likely to hire movers, especially those coming from lower-paying, neighboring occupations. Fourth, a counterfactual decomposition of the effect of tightness on realized transitions suggests that firm behavior accounts for approximately one-third of the increase in occupational mobility in tight relative to slack occupations.

Overall, our study highlights that firms’ willingness to hire movers depends on the overlap of job requirements between occupations, occupational experience, qualifications, and labor market tightness. By characterizing how these factors interact to shape cross-occupational mobility, this paper’s key contribution is to shed light on firms’ role in occupational transitions. These insights are not only academically relevant but also inform the design of job training and placement programs that help job seekers transition into in-demand occupations. They can also help policymakers devise strategies to alleviate labor and skill shortages in critical occupations.

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Online Appendix

Adapting to Scarcity: The Role of Firms in Occupational Transitions

A Data Details: Job-Room Data

Figure A.1: Screenshot of Candidate Profile on Job-Room, German

Berufe, Qualifikationen und Erfahrungen des Kandidaten	
Zuletzt ausgeübter Beruf:	Betriebsarbeiter
Erfahrungsjahre auf dem Beruf:	mehr als 1 Jahr
Berufsbezeichnung:	Automechaniker
Abschluss zum Beruf:	ausländisch, CH nicht anerkannt
Erfahrungsjahre auf dem Beruf:	mehr als 3 Jahre
Kenntnisse, Fähigkeiten, Skills:	Ausbildung in Mazedonien
Berufsbezeichnung:	Bauhandlanger
Erfahrungsjahre auf dem Beruf:	mehr als 1 Jahr
Sprachkenntnisse des Kandidaten	
Deutsch:	mündlich: gut, schriftlich: Grundkenntnisse
Albanisch:	mündlich: sehr gut, schriftlich: sehr gut
Weitere Angaben des Kandidaten	
Verfügbarkeit:	nach Vereinbarung
Arbeitsform:	keine Angabe
Geschlecht:	männlich
Maximales Arbeitspensum:	100%
Mögliche Anstellungsdauer:	unbefristet
Höchste Bildungsstufe:	Sekundarstufe II - ISCED 3
Ausbildung:	Sek. II - Berufliche Grundbildung EFZ od. äq. Sek. I - obligatorische Schule
Gesuchte Arbeitsregion/en:	Grossregion 4 (ZH, SH, TG, SG, AI, AR, GL, GR)
Führerausweiskategorien:	B
Weitere Auskünfte erteilt:	
Adresse:	RAV Frauenfeld, Thundorferstrasse 37, 8510 Frauenfeld Kant. Verwaltung
<input type="button" value="Kontaktdaten anzeigen"/>	
<input type="button" value="Zurück"/> <input type="button" value="Diesen Kandidat als Link senden"/> <input type="button" value="Druckansicht"/>	

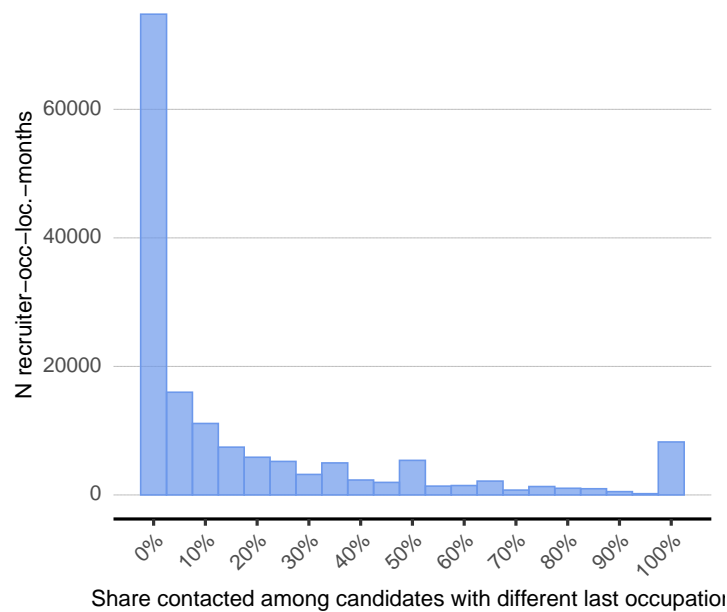
Notes: The figure shows a screenshot of the full candidate profile on Job-Room as seen by a recruiter.

Table A.1: Distribution of recruiter searches over broad occupation groups.

Occupation group	N recruiter searches
Managers	3633
Professionals	30754
Technicians and associate professionals	41838
Clerical support workers	27757
Service and sales workers	22088
Skilled agricultural, forestry and fishery workers	11354
Craft and related trades workers	213945
Plant and machine operators and assemblers	26727
Elementary occupations	28777

Notes: The figure shows the number of recruiter searches by searched occupation, aggregated at the ISCO-19 one-digit level.

Figure A.2: Distribution of the contact rate among candidates from a different occupation



Notes: The figure shows the share of candidates whose last occupation is different from the recruiter's searched occupation that are contacted by the recruiter. The level of observation is a recruiter-month-search criteria combination where search criteria denotes the combination of the searched occupation and the searched location. The sample is restricted to observations with at least one contacted candidate.

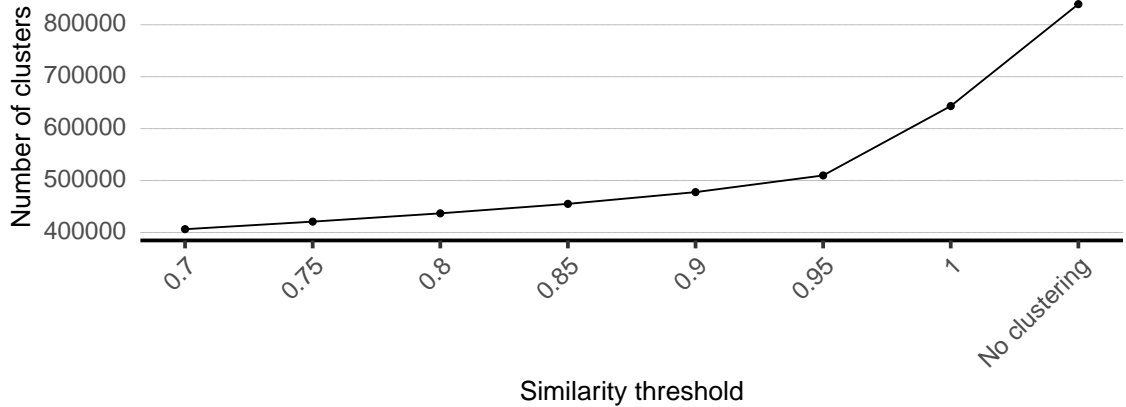


Figure A.3: Elbow plot displaying the number of clusters as a function of the similarity threshold used in hierarchical clustering of commercial register entries. The inflection point around 0.95 guides the choice of threshold for defining firm-level clusters.

A.1 Matching firm names from the application to the name of the re-employment firm

To assign free-text employer names to consistent firm identifiers, we implement a two-stage procedure involving (1) string matching from survey data to firms in the commercial register, followed by (2) clustering of similar firm entries within the commercial register itself. This second step is crucial: while official registers list legal entities, they often include multiple entries for what is essentially the same firm group (e.g., divisions, regional subsidiaries, or holding entities with nearly identical names). While the string matching provides good matches for similar entries in the register, in cases where a firm has more than one similar-sounding legal entity, it lacks the precision to pick the right one. Our clustering thus creates higher-level entities that group these entries, and we match two firms if they belong to the same group. This procedure has the additional advantage that we can use the groups for firm-fixed effects.

In the string matching used for both stages, we follow the approach developed by Brüll (2025); Brüll et al. (2025). Firm names are normalized by uppercasing and removing non-alphanumeric characters (while preserving diacritics), then tokenized into word-like units. We drop tokens that are too common (i.e., appearing in more than 1 in 500 firms), since these provide little discriminatory power. The identification potential of each token is then calculated as the token’s inverse frequency, normalized to sum to one within each name. Intuitively, this gives higher weight to distinctive words in a name (e.g., “NOVARTIS” vs. “LTD”). For the clustering of firm entities within the commercial register, we apply hierarchical clustering with complete linkage and a minimum similarity threshold of 0.95, ensuring that only highly similar entries are grouped together (see Figure A.3 for a plot of the number of clusters for different thresholds).

To further enhance precision, we incorporate a curated dictionary of firm-related

Table A.2: Job seeker profile control variables

Variable	Description
<i>Demographics and Availability</i>	
Gender: Male/Female	Gender of the job seeker
Availability	Immediately available or no information
Protected contact information	Contact details hidden from recruiters
<i>Work Preferences</i>	
Willing to work shifts	Accepts shift work
Willing to work nights	Accepts night work
Willing to work Sundays/holidays	Accepts weekend/holiday work
Willing to work from home	Accepts remote work
Willing to do apprenticeship	Open to apprenticeship positions
Desired work volume	<50%, 50%-90%, or full-time
Contract type	Preference for temporary or permanent contract
<i>Geographic Mobility</i>	
Canton-specific willingness	Willing to work in a canton incl. a major city: ZH, BE, BS, VD, GE (5 dummies)
Geographic mobility	Number of cantons (0, 2-4, 5-7, 8-26)
<i>Language Competencies</i>	
German	Basic, Good, or Very good
French	Basic, Good, or Very good
Italian	Basic, Good, or Very good
English	Basic, Good, or Very good
Other languages	Basic, Good, or Very good
<i>Education and Experience</i>	
Education level	Primary, Secondary/vocational, or University
Number of occupations listed	Count of different professions in profile
<i>Skills Field Text Analysis</i>	
Education mentions	General, tertiary, vocational, or continuing education
Skills mentioned	Soft skills, IT (general/advanced), machine operation, leadership, languages
Experience duration	1-5, 6-10, 10-20, or >20 years
Text characteristics	Language used (German/Italian/other), word count (1-10, 11-20, 21-30, >30)

Notes: This table lists all job seeker-specific control variables extracted from candidate profiles on the Swiss Public Employment Service platform (Job-Room). These variables capture the information visible to recruiters when browsing candidate profiles. Variables prefixed with "Skills" are extracted from the free-text skills field using text analysis methods. Canton abbreviations: ZH (Zurich), BE (Bern), BS (Basel-Stadt), VD (Vaud), GE (Geneva).

lexical tokens, constructed through a large-scale classification exercise using OpenAI's GPT 3.5 model. Specifically, we submitted all unique employer names from both "applied to" and "clicked" fields in the survey data and prompted the model to identify whether they correspond to known firm entities. Tokens identified as unambiguous firm markers were assigned maximum identification potential. The list is available in the supplementary data files.

To validate the method, we use a hand-labelled dataset of 2,000 matched name pairs. The procedure achieves balanced accuracy of 91.9%, with sensitivity of 98.97% and specificity of 84.77%, showing that our approach reliably identifies consistent firm groups from noisy free-text data.

B Data Details: Online Search Diaries

Figure B.1: Application protocol data: Online submission form

Wann haben Sie sich beworben?

Date: 15.05.2024

Wie haben Sie sich beworben?

Elektronisch
 Brieflich
 Persönlich
 Telefonisch

Wo haben Sie sich beworben?

Business: Coop Genossenschaft

Street: No. 81 characters available

PO box no. 100 characters available

Country: Switzerland

Postal code / city: 100 characters available

Kontaktperson: 100 characters available

Email: muster@example.org

Link zum Online-Formular: www.example.org/stelle-xy

Phone number: 031 999 99 99 or +41 31 999 99 99

Auf welche Stelle haben Sie sich beworben?

job title: Köchin / Koch (w/m/d) 79 characters available

Erfolgte die Bewerbung aufgrund einer Zuweisung des RAV?

No
 Yes

Für welches Arbeitspensum haben Sie sich beworben?

Vollzeit
 Teilzeit

Wie lautet das Ergebnis Ihrer Bewerbung?

Vorstellungsgespräch
 Noch offen
 Anstellung
 Absage

Bitte beachten Sie die wichtigen Hinweise bezüglich ihrer Pflichten!

Cancel Save

(a) Application protocols: Application entry form

Nachweis der persönlichen Arbeitsbemühungen Filtern

This page is only available in the official Swiss languages German, French and Italian.

Search for already entered company or job description

▲ Mai 2024	NpA_2024-05.pdf	Bearbeitungsstatus Anzahl erfasst: 2	Übermittlungsstatus Manuelle Übermittlung möglich ab 27.05.2024
Bewerbung vom 09.05.2024 Company CEO	Ergebnis der Bewerbung <input checked="" type="checkbox"/> Vorstellungsgespräch <input checked="" type="radio"/> Noch offen <input type="radio"/> Anstellung <input type="radio"/> Absage	Bearbeitungsstatus Gespeichert am 15.05.2024	Übermittlungsstatus Automatische Übermittlung erfolgt am 06.06.2024 um 00:00 Uhr
Bewerbung vom 10.05.2024 Company 2 Accountant	Ergebnis der Bewerbung <input checked="" type="checkbox"/> Vorstellungsgespräch <input type="radio"/> Noch offen <input type="radio"/> Anstellung <input checked="" type="radio"/> Absage	Bearbeitungsstatus Gespeichert am 15.05.2024	Übermittlungsstatus Automatische Übermittlung erfolgt am 06.06.2024 um 00:00 Uhr

(b) Application protocols: Overview of monthly proof of effort

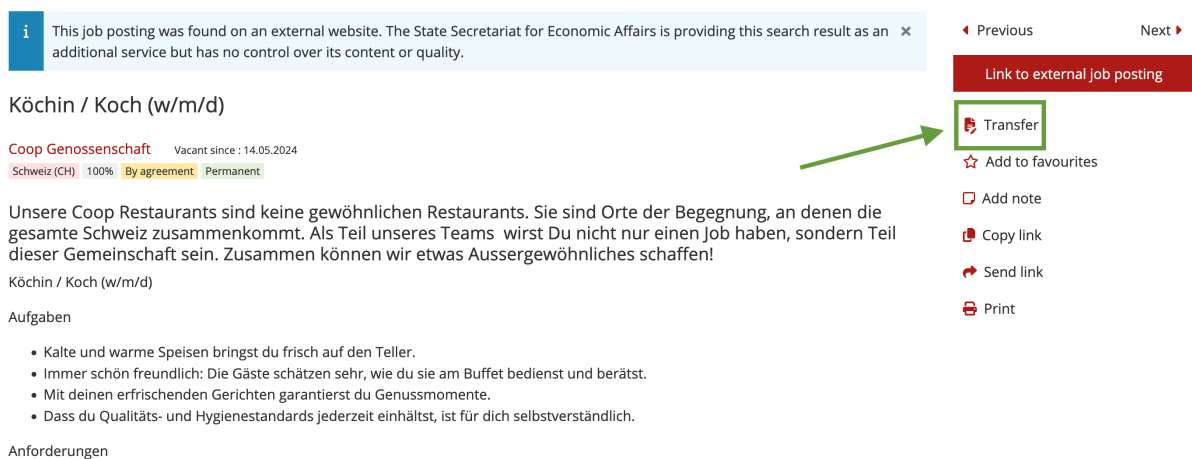
Notes: The figure shows screenshots of the two relevant online forms to report the monthly application efforts to the Swiss PES.

Table B.1: Descriptive statistics of job seekers using the application feature: completed spells only

	All spells (N = 178 436)		Sample (N = 12 230)	
	Mean	SD	Mean	SD
Female	0.45	0.50	0.50	0.50
Age (at registration)	38.96	11.53	38.81	11.14
Primary education	0.29	0.45	0.27	0.44
Secondary or vocational educ.	0.48	0.50	0.55	0.50
University education	0.16	0.37	0.13	0.33
Non-permanent resident	0.25	0.44	0.27	0.44
> 3 years tenure in last job	0.67	0.47	0.66	0.47
Insured earnings (CHF)	5078.60	2478.61	4792.11	2244.54
Reemployment occ. different from last occ.	0.53	0.50	0.58	0.49

Notes: This table shows the composition of the sample of job seekers with completed spells and known re-employment companies that use the feature allowing them to transfer the information from a Job-Room vacancy to their monthly application protocol. As a comparison, the population of unemployment spells active in 2022 and completed with a known re-employment company is shown.

Figure B.2: Application protocol data: Transfer link on job ad



Notes: The figure shows a screenshot from the job platform functionality of the Job-Room, the job board of the Swiss PES. The screenshot highlights the transfer button that allows job seekers to import the data from the respective job opening to their monthly application protocols (search diaries).

C Details on the Index of Overlap in Job Requirements

C.1 Vacancy Data

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

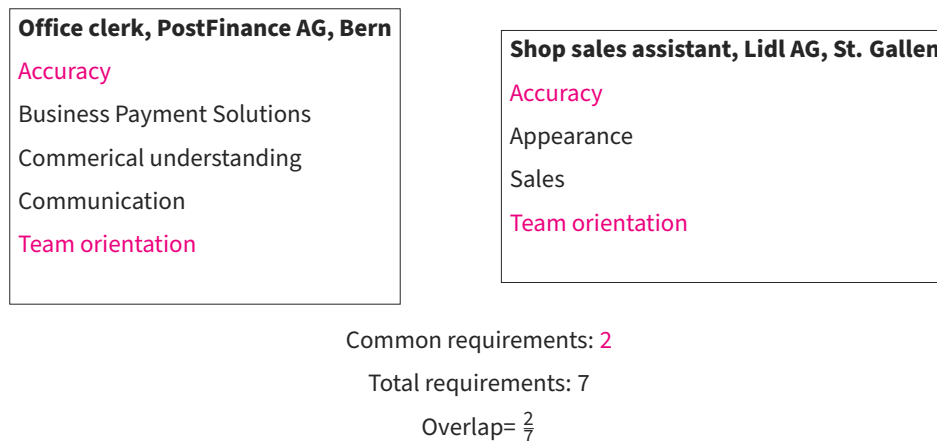
A key feature of the data—and one it shares with similar vacancy datasets in other countries—is that it comes with a list of job requirements extracted from the text and job title of each ad. x28 extracts these requirements by matching the text to keywords from a large, manually and continuously maintained database of terms related to the task and skill requirements of jobs. The granular ontology distinguishes between 23,592 different skills or tasks; we restrict our sample to the 1,087 that appear at least once per 5,000 ads. It includes both soft and hard skills and education requirements. Examples of job requirements include “accuracy”, “commercial understanding”, “sales skills”, “team orientation”, or various IT skills (e.g., knowledge of Python or SAP).

C.2 Index Computation

We compute the overlap in job requirements between two occupations in two steps.

First, we randomly select pairs of vacancy postings for each of the occupation pairs that we compare. We then calculate the overlap in job requirements for the pair based on their Jaccard similarity: the number of job requirements mentioned by both vacancies relative to the total number of distinct job requirements mentioned in both job vacancies. Figure C.1 shows a stylized example for an office clerk and shop sales assistant position. The two vacancies list a total of seven distinct job requirements: accuracy, business payment solutions, commercial understanding, communication, team orientation, appearance, and sales. Two of these job requirements are mentioned in both job vacancies: accuracy and team orientation. Thus, the Jaccard similarity of the two vacancies—the ratio between the common requirements relative to the seven distinct requirements—is $\frac{2}{7}$.

Figure C.1: Job Requirements Overlap Example



Notes: This figure illustrates job requirements overlap between two example vacancies.

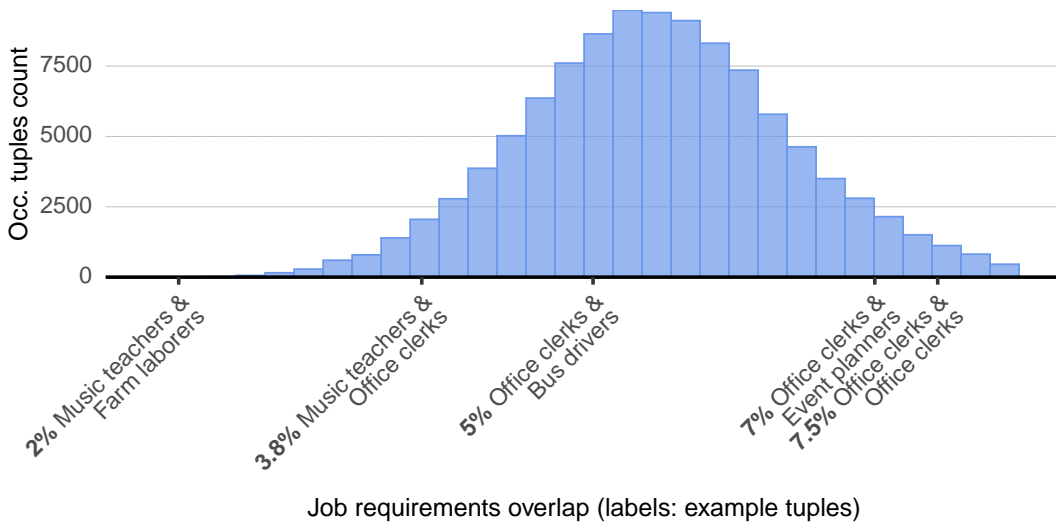
The second step in the construction of our overlap measure is to repeat step 1 for 5000 randomly drawn vacancy pairs and then average the estimated Jaccard similarities over the randomly drawn pairs of job vacancies. To do so, we sample one vacancy from occupation A (with replacement) and one from occupation B (with replacement) and repeat this step 5000 times. Intuitively, the measure captures the average overlap in the job requirements of two occupations. A distinct advantage of this procedure is that we can calculate the similarity within an occupation, too, as we can simply compute the Jaccard similarity for 5000 randomly drawn vacancy pairs from the same occupation.

When computing the index, we only consider occupations with at least 200 posted vacancies between 2016 and mid-2022. This sample covers 80% of all possible ISCO four-digit tuples.

C.3 Imputation of Missing Overlap for Recruiter Analysis

The sample restriction implies that we lack an overlap value for certain occupation pairs. Out of the 15 266 233 recruiter search results, 410 429 observations (approximately 2.7%) lack a job requirements overlap value. To avoid losing these observations in the empirical analyses, we implement a hierarchical imputation strategy based on the ISCO classification structure. We impute these in three steps, using progressively broader ISCO groupings. First, we replace missing values with the average job requirements overlap between occupation pairs that share the same three-digit ISCO group, which resolves the majority of cases. For the remaining 310 804 observations, we impute based on averages within the two-digit ISCO group. Finally, the remaining 95 missing values are imputed using averages at the one-digit level.

Figure C.2: Distribution of job requirements overlap over occupation tuples



Notes: This figure reports a histogram of job requirements overlap between all tuples of occupations.

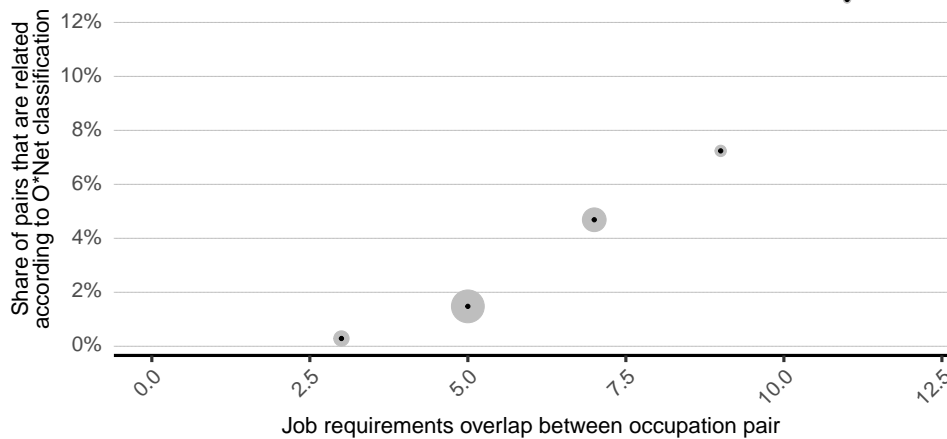
C.4 Job Requirements Within and Across Occupation

Figure C.2 shows the distribution of job requirements overlap across all occupation pairs. On the x-axis, we illustrate the similarity index of office clerks to five other occupations. As expected, jobs for office clerks are most similar to other jobs that advertise for office clerks. Two randomly drawn vacancies within this occupation share on average 7.5% of their job requirements. On the other extreme, office clerks and music teachers are quite distinct. The most distinct pair is farm laborers and music teachers. On average, they have only 2% of job requirements in common. Finally, office clerks’ positions are quite similar to event planner positions. The average overlap in job requirements is around 7% for these two occupations.

C.5 Validation of Overlap Index: Comparison to O*Net

In this section, we validate our measure of job requirements overlap by comparing it with the O*Net classification of related occupations. O*Net is maintained by the U.S. Department of Labor and is a comprehensive database that describes occupations based on detailed surveys and expert analysis. The O*Net database identifies ten related occupations for each occupation. O*Net provides three relatedness tiers, ‘primary-long’, ‘primary-short’, and ‘supplemental’; we focus on the primary tiers. The relatedness composite is an average based on three dimensions. First, a measure of the similarity between two occupations in tasks and work activities, based on the O*Net database of these items. Second, the similarity in the knowledge required to perform the job, a high-level measure of 34 topics such as “administration,” “business and accounting,” or “sales and marketing,” also from its own database. The third part is the similarity of job titles based on a

Figure C.3: Job Requirements Overlap compared to the O*Net “Related occupations”



Notes: The figure shows a binned scatter plot plotting the share of related occupations according to O*Net against our overlap measure. We map O*NET SOC-2019 codes to ISCO-19 codes via a two-step crosswalk: first from SOC-2019 to SOC-2010, and then from SOC-2010 to ISCO-19. We further weight SOC-2019 occupations by their U.S. employment shares to account for the relevance of each occupation (shares are obtained from the Occupational Employment Statistics survey, following Belot et al. (2019)). A pair of ISCO-19 occupations is labeled as “related” if at least one of their corresponding SOC-2019 codes is marked as related in ONET. We then compute, for each ISCO-19 pair in our similarity index, the weighted share of “related” links based on this mapping.

word embedding model.

Figure C.3 presents a binned scatter plot showing the relationship between our measure of job requirements overlap and the O*Net classification of related occupations. The x-axis represents the job requirements overlap between pairs of occupations, measured using the Jaccard similarity index described in the previous sections. The y-axis indicates the share of occupation pairs that are classified as related according to O*Net. Each dot in the plot corresponds to a bin of job requirements overlap values, with the size of the dot representing the number of observations within that bin. There is a clear positive correlation between our measure of job requirements overlap and the O*Net classification. As the overlap in job requirements increases, the likelihood that two occupations are classified as related by O*Net also increases. This indicates that our measure captures similar dimensions of job similarity as the O*Net classification. The O*Net classification, while thorough, is limited to identifying a fixed number of related occupations. In contrast, our measure provides a continuous scale of similarity that captures a more nuanced and detailed picture of how job requirements overlap between occupations. This is particularly useful for distinguishing between occupations that might not be captured as related in the discrete O*Net framework but show significant overlap in job requirements. The comparison validates our approach by demonstrating that our data-driven measure aligns well with an established classification system.

D Measuring Tightness

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

For each occupation-region cell, we measure tightness as the monthly average number of online vacancies divided by the average number of unemployed job seekers. Formally,

$$tightness_{o,c,t} = \frac{V_{o,c,t}}{U_{o,c,t}} \quad (6)$$

where $V_{o,c,t}$ represents the stock of online vacancies in occupation o and region \mathcal{C} in the 30-day rolling average around day t . The data come from the private firm x28 and cover the near-universe of online vacancies posted on job boards and firm websites in Switzerland (see section C.1 for a description). Similarly, $U_{o,c,t}$ represents the average number of job seekers registered as unemployed in the 30 days around day t that last worked in occupation o and look for a job in region \mathcal{C} . These data stem from the Swiss unemployment register. Since the empirical analyses are based on the log of $tightness_{o,c,t}$, we lose a small number of observations because either $V_{o,c,t}$ or $U_{o,c,t}$ are zero in a certain month.

We assign the tightness measure to recruiters in the following way: o represents recruiters' searched occupation, d the day of the search, and \mathcal{C} is the canton (or one of 7 broader regions, each comprising a list of cantons) that 80% of recruiters specify when searching for a candidate on Job-Room. For recruiters who do not restrict their search regionally, the search region is defined as Switzerland as a whole.

Figure D.1 shows the distributions of the logarithm of our tightness measure for recruiters. The figure illustrates the substantial variation in tightness in our sample. Figure D.3 shows the evolution of occupational labor market tightness at the occupation-location level over time. The figure plots the 25th percentile, mean, and 75th percentile of these log-differenced tightness values across all occupation-location cells in each month. The divergence in the different indices reveals that, despite the short sample period, there is substantial variation in the evolution of tightness in different labor markets defined by the combination of region and occupation.

Figure D.1: Distribution of the tightness measure

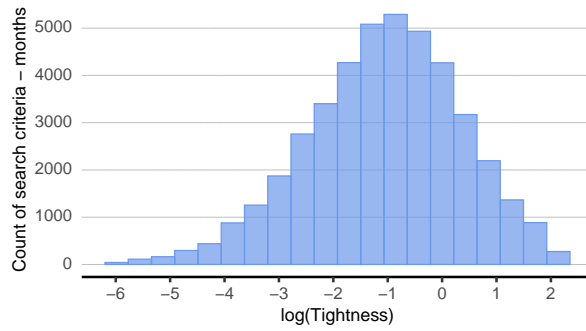
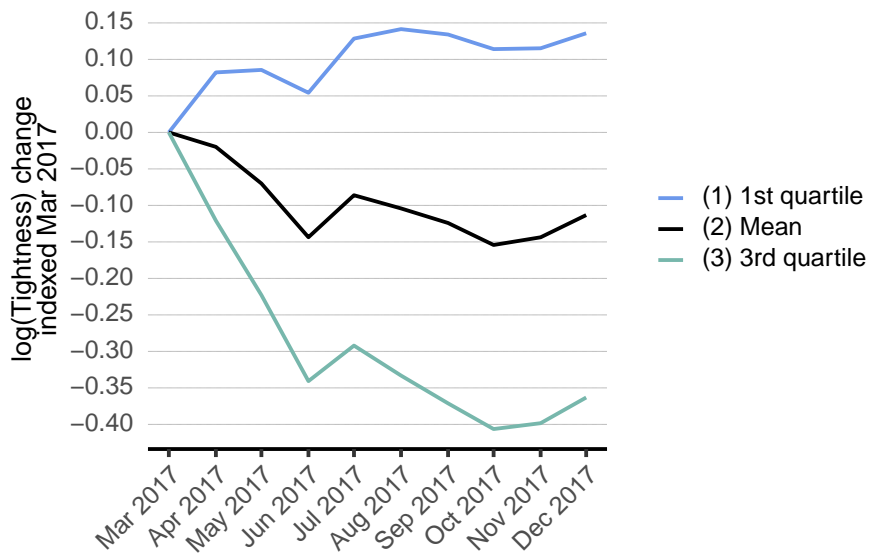


Figure D.2: Recruiters

Notes: The plot shows a histogram of the log tightness of recruiters' searched markets (occupation \times location) in different months.

Figure D.3: Temporal variation in labor market tightness across occupation-region cells



Notes: This figure shows the evolution of occupational labor market tightness at the occupation-region level over time. Each occupation-location series is indexed by subtracting its log tightness in the initial month (March 2017). The figure plots the 25th percentile, mean, and 75th percentile of these log-differenced tightness values across all occupation-region cells in each month.

Table E.1: Robustness checks: The contact penalty of job seekers from a different occupation

	Baseline	3-digit ISCO	Less than 20s	Concrete interest
	(1)	(2)	(3)	(4)
Dependent Var.:	Contact click	Contact click	Contact click	Mail or print or fav.
Coefficient	-0.0077*** (0.0003)	-0.0076*** (0.0003)	-0.0028*** (0.0002)	-0.0023*** (0.0001)
Effect relative to baseline (%)	-7.0299	-6.8939	-4.5510	-12.4592
Candidate FE	X	X	X	X
Recruiter search FE	X	X	X	X
Search rank (abs. and rel.) FE	X	X	X	X
-----	-----	-----	-----	-----
Observations	15,266,233	15,266,233	14,221,859	15,266,233
R2	0.46442	0.46442	0.47637	0.31158
N searches	406,873	406,873	387,393	406,873
N recruiters	37,665	37,665	37,043	37,665
Baseline prob.	0.1100	0.1100	0.0618	0.0184
Sample	All	All	Less than 20s	All

Notes: This table presents robustness checks for the baseline results from Table 3. Column (1) replicates the baseline specification using the 4-digit ISCO classification. Column (2) uses a three-digit ISCO classification to define occupational similarity. Column (3) restricts the sample to cases where recruiters spent at most 20 seconds viewing the candidate's profile. Column (4) uses an alternative outcome variable that combines concrete indicators of recruiter interest (printing the profile, clicking on email contact, or adding to favorites) instead of the contact button click. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the recruiter level.

E Further Results and Tables

Table E.2: Determinants of the penalty for job seekers from a different occupation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Last worked in different occupation	-0.0077*** (0.0003)	-0.0031*** (0.0004)	-0.0068*** (0.0003)	-0.0027*** (0.0007)	-0.0072*** (0.0004)	0.0024** (0.0010)	0.0015 (0.0018)
Last worked in almost similar occ.		-0.0014*** (0.0005)				-0.0014*** (0.0005)	-0.0011 (0.0010)
Last worked in quite similar occ.		-0.0044*** (0.0006)				-0.0042*** (0.0007)	-0.0025* (0.0013)
Last worked in quite dissimilar occ.		-0.0069*** (0.0008)				-0.0064*** (0.0008)	-0.0052*** (0.0015)
Last worked in dissimilar occ.		-0.0078*** (0.0009)				-0.0079*** (0.0009)	-0.0044*** (0.0016)
Last worked in very dissimilar occ.		-0.0091*** (0.0008)				-0.0079*** (0.0008)	-0.0029 (0.0018)
No experience in searched occ.			-0.0059*** (0.0005)	-0.0101*** (0.0009)		-0.0097*** (0.0009)	-0.0104*** (0.0017)
No prof. qualification in searched occ.			-0.0041*** (0.0004)			-0.0038*** (0.0004)	-0.0065*** (0.0008)
Experience in searched occ. is at least 1y old				-0.0025*** (0.0009)		-0.0025*** (0.0009)	-0.0023 (0.0020)
Experience in searched occ. is at least 3y old				-0.0052*** (0.0008)		-0.0052*** (0.0008)	-0.0061*** (0.0016)
Last worked in higher-paid occ.					-0.0011** (0.0005)	-0.0014** (0.0006)	-0.0023** (0.0011)
Last worked in diff occ. x 35-45y old							0.0010 (0.0011)
Last worked in diff occ. x 50y old							0.0017 (0.0011)
Recruiter search FE	X	X	X	X	X	X	X
Search rank (abs. and rel.) FE	X	X	X	X	X	X	X
Candidate FE	X	X	X	X	X	X	X
-----	-----	-----	-----	-----	-----	-----	-----
Observations	15,266,233	15,004,682	14,927,811	15,266,233	15,265,978	14,671,870	4,475,077
R2	0.46442	0.46506	0.46513	0.46443	0.46442	0.46579	0.50972
N searches	406,873	406,873	406,873	406,873	406,873	406,873	406,873
N recruiters	37,665	37,665	37,665	37,665	37,665	37,665	37,665
Baseline prob.	0.1100	0.1100	0.1100	0.1100	0.1100	0.1100	0.1100

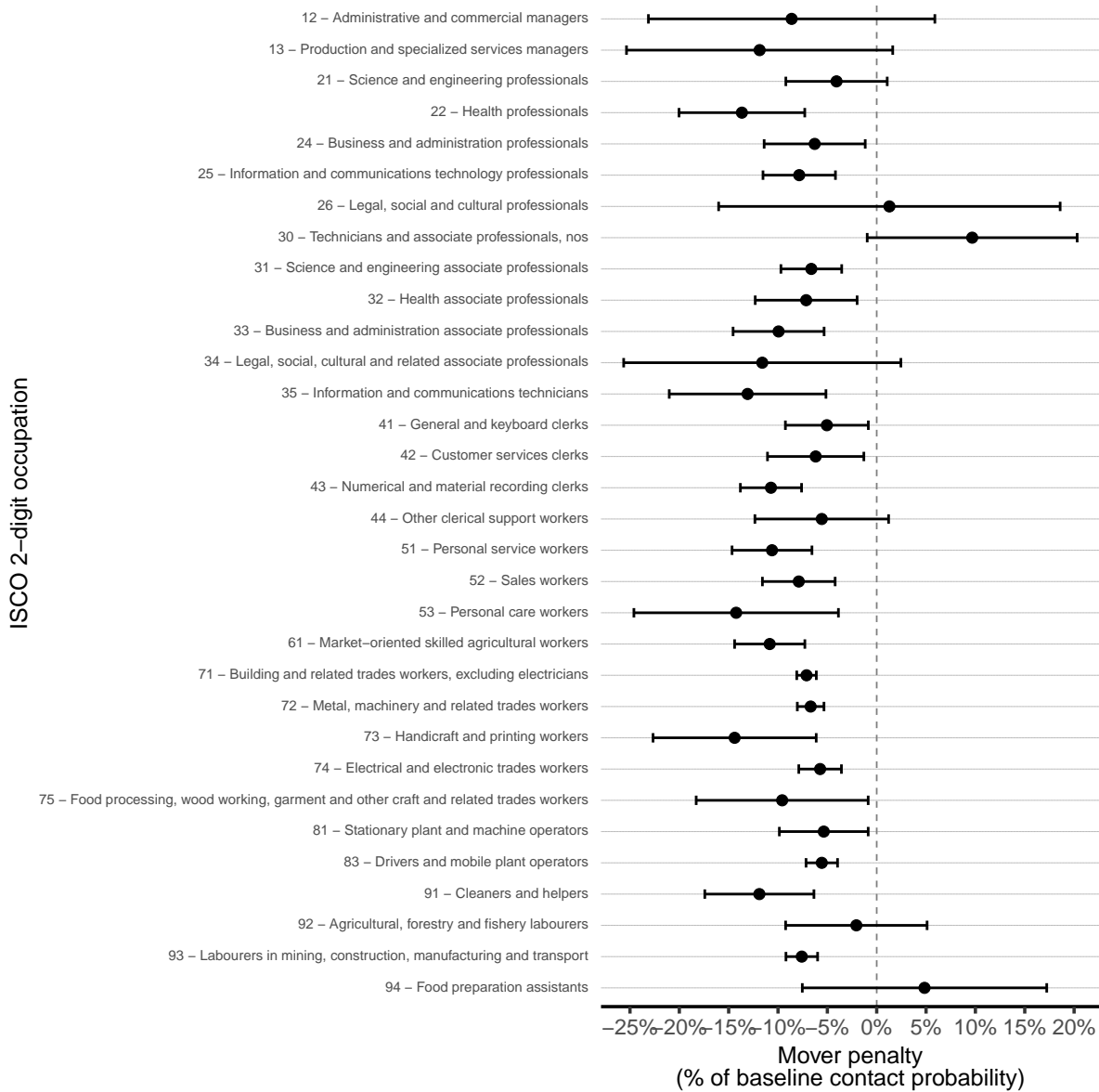
Notes: This table tests different mechanisms why job seekers from a different occupation face a contact penalty on Job-Room. The outcome is whether the recruiter clicks on the button to reveal a candidate's contact details. The main regressor is whether the occupation of the candidate's last employment is different from the occupation the recruiter entered as a search term. Each observation represents a candidate profile that appeared as a result of a recruiter's search. The distance between two occupations is measured using the overlap in job requirements between two average vacancies in the two occupations (see Section 5.1.1). We compute the difference in overlap between job ads in the searched occupation and the last occupation, and subtract from this the overlap in two job ads in the searched occupation. The categories represent dummies for the percentage point difference starting at 0 (reference category) and going to -5 or lower ('very dissimilar'). The measure is expressed in percentage point units. The variable "last worked in higher-paid occupation" is an indicator that the job seeker last worked in an occupation with a higher median wage than the recruiters' searched occupation. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the recruiter level.

Table E.3: Heterogeneity in the mover penalty by searched occupation categories

	(1)	(2)	(3)	(4)	(5)
DO = 1 (Last worked in different occupation)	-0.0077*** (0.0003)	-0.0081*** (0.0005)	-0.0085*** (0.0004)	-0.0044*** (0.0005)	-0.0062*** (0.0007)
DO = 1 x Medium wage occ.		-0.0025*** (0.0008)			-0.0004 (0.0008)
DO = 1 x High wage occ.		0.0031*** (0.0006)			0.0016** (0.0008)
DO = 1 x Primary education			0.0002 (0.0007)		0.0012 (0.0007)
DO = 1 x University education			0.0060*** (0.0007)		0.0031*** (0.0008)
DO = 1 x Medium within-occ. requirements overlap				-0.0035*** (0.0007)	-0.0028*** (0.0007)
DO = 1 x High within-occ. requirements overlap				-0.0067*** (0.0008)	-0.0053*** (0.0009)
Candidate FE	X	X	X	X	X
Recruiter search FE	X	X	X	X	X
Search rank (abs. and rel.) FE	X	X	X	X	X
-----	-----	-----	-----	-----	-----
Observations	15,266,233	15,266,232	15,266,202	15,004,682	15,004,653
R2	0.46442	0.46442	0.46442	0.46505	0.46505
N searches	406,873	406,873	406,873	406,873	406,873
N recruiters	37,665	37,665	37,665	37,665	37,665
Baseline prob.	0.1100	0.1100	0.1100	0.1100	0.1100

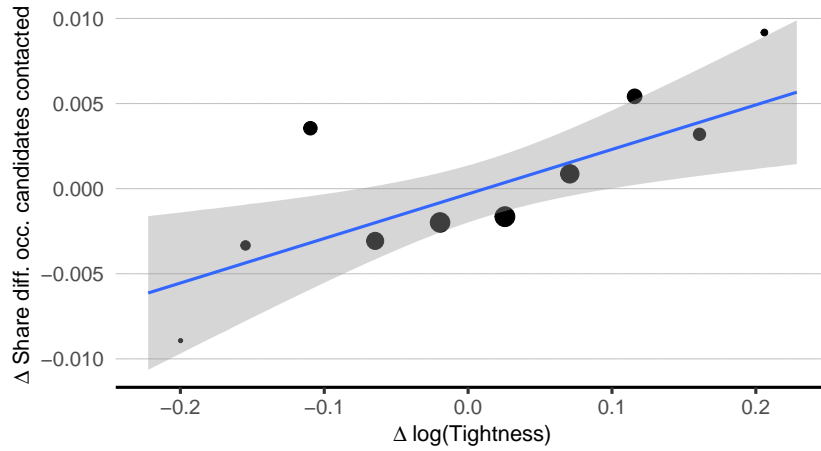
Notes: This table tests whether the contact penalty job seekers from a different occupation face on Job-Room differs by characteristics of the searched occupation. The outcome is whether the recruiter clicks on the button to reveal a candidate's contact details. The main regressor is whether the occupation of the candidate's last employment is different from the occupation the recruiter entered as a search term. Each observation represents a candidate profile that appeared as a result of a recruiter's search. Column (1) is the baseline specification from Table 3, Column (1). Column (2) interacts the penalty with the median wage in the recruiter's searched occupation obtained from the Swiss Earnings Structure Survey (ESS), split into three equally sized groups. The reference group is the group with the lowest wage level. Column (3) interacts the penalty with the typical level of education of an incumbent candidate in the recruiter's searched occupation. The reference category is secondary or vocational education. Column (4) interacts the penalty with the job requirements overlap *within* the recruiter's searched occupation, measuring homogeneity of the occupation with respect to job requirements. The measure is divided into three equally sized groups; the group with the lowest homogeneity is the reference group. Column (5) adds all three dimensions jointly. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the recruiter level.

Figure E.1: Heterogeneity in the mover penalty by broad searched occupation



Notes: This figure shows the contact penalty job seekers from a different occupation face on Job-Room interacted with the recruiter’s searched occupation, aggregated at the ISCO 2-digit level. The rest of the specification follows the baseline specification in Table 3, Column (1). The outcome is whether the recruiter clicks on the button to reveal a candidate’s contact details. The main regressor is whether the occupation of the candidate’s last employment is different from the occupation the recruiter entered as a search term. The effect is shown relative to the occupation-specific baseline contact probability. Each observation represents a candidate profile that appeared as a result of a recruiter’s search. Only 2-digit level occupations with at least 1000 searches are included (402 417 out of 406 873 searches). Standard errors are clustered at the recruiter level, 95% confidence intervals are shown.

Figure E.2: Within occupation-location relationship between tightness and recruiters' occupational openness.



Notes: The figure shows a binned scatter plot of the relationship between labor market tightness and the share of candidates who last worked in a different occupation than the one searched by the recruiter that were contacted by the recruiter. Both variables are demeaned within occupation-canton group cells. The demeaned $\log(\text{tightness})$ is winsorized at the 5th and 95th percentiles. Each observation represents a unique combination of recruiter, search month, searched occupation, and searched location (i.e., recruiter-month-“cell”). The tightness is measured at the monthly level in the searched occupation-location cell, computed as the average daily stock of vacancies divided by the average daily stock of incumbent job seekers. The searched location can be a canton, a combination of cantons, or the whole of Switzerland if no location filter is chosen. See Appendix D for details. The sample is restricted to recruiter-month observations with at least one resulting candidate from a different occupation. The dot size is proportional to the number of observations in the bin.

Table E.4: Effect of tightness in recruiters' searched occupation on the composition of search results

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	N profiles found	N found diff. occ	Share of results diff occ.	N profiles viewed	Share of views diff occ.
log(Tightness)	-0.0779*** (0.0209)	0.0228 (0.0223)	0.0408*** (0.0048)	-0.0120 (0.0316)	0.0426*** (0.0063)
Calendar month FE	X	X	X	X	X
Searched occ. x canton scope FE	X	X	X	X	X
Recruiter FE	X	X	X	X	X
Family	Poisson	Poisson	OLS	Poisson	OLS
Sample	All searches	All searches	All searches	All searches	Cond. on 1+ profile view
Observations	401,670	401,670	401,670	401,670	336,282
Number of recruiters	37,288	37,288	37,288	37,288	34,295
Pseudo R2 / R2	0.4525	0.4483	0.4003	0.3461	0.3148
Mean of dependent var.	37.56	17.87	0.4585	9.159	0.4496

Notes: This table shows regression estimates based on Equation (3) of the impact of tightness on recruiters' occupational scope. The estimates are from Poisson and OLS regressions where each observation represents a unique combination of recruiter, search month, searched occupation, and searched location (i.e., recruiter-month-“cell”). Only combinations with at least one search over the whole sample period are included. The tightness is measured at the monthly level in the searched occupation-location cell, computed as the average daily stock of vacancies divided by the average daily stock of incumbent job seekers. The searched location can be a canton, a combination of cantons, or the whole of Switzerland if no location filter is chosen. See Appendix D for details. Standard errors are clustered at the recruiter level. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table E.5: Robustness to zeroes in the tightness measure: Effect of tightness in recruiters' searched occupation on their search behavior

	(1)	(2)	(3)	(4)	(5)	(6)
	N contacts	P(DO=1 contact)	E[overlap contact]	P(D==1)	P(contact DO=1)	P(contact)
log(Tightness)	0.6852*** (0.0968)	0.0418*** (0.0086)	-0.3435*** (0.0480)	0.0412*** (0.0050)	0.0193*** (0.0065)	0.0212*** (0.0064)
Calendar month FE	X	X	X	X	X	X
Searched occ. x canton scope FE	X	X	X	X	X	X
Recruiter FE	X	X	X	X	X	X
Family	Poisson	OLS	OLS	OLS	OLS	OLS
Observations	1,338,950	114,837	114,837	164,114	156,263	164,114
Mean of dependent var.	1.25386	0.42541	9.30507	0.48612	0.17849	0.20551
Number of recruiters	37,665	23,690	23,690	37,665	37,022	37,665
Pseudo R2 / R2	0.3258	0.4662	0.7502	0.5405	0.4884	0.5143

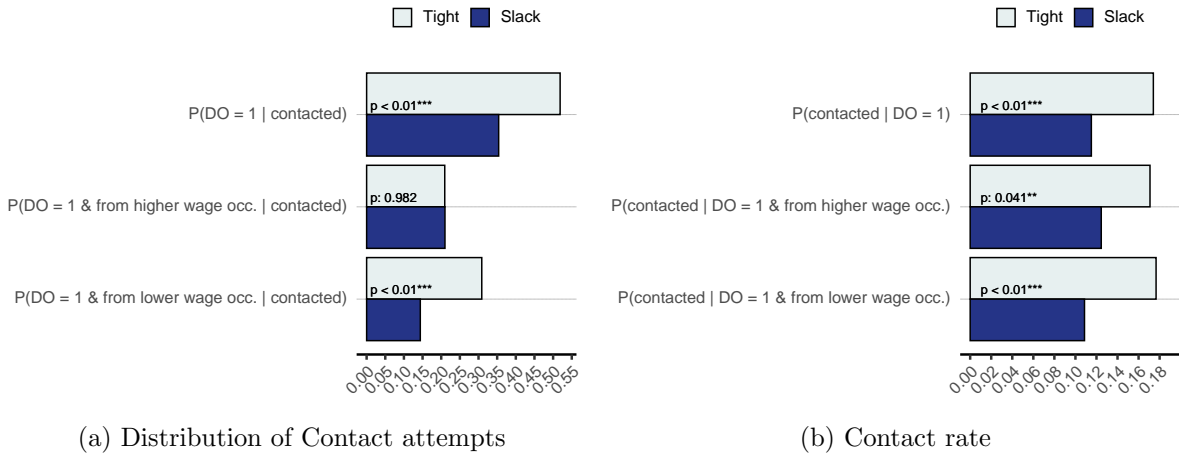
Notes: This table shows regression estimates based on Equation (3) of the impact of tightness on recruiters' openness to job seekers with different occupational backgrounds. Monthly vacancy counts or job seeker averages with a value of zero are imputed with a value of one. The estimates are from Poisson and OLS regressions where each observation represents a unique combination of recruiter, search month, searched occupation, and searched location (i.e., recruiter-month-“cell”). Only combinations with at least one search over the whole sample period are included. The tightness is measured at the monthly level in the searched occupation-location cell, computed as the average daily stock of vacancies divided by the average daily stock of incumbent job seekers. The searched location can be a canton, a combination of cantons, or the whole of Switzerland if no location filter is chosen. See Appendix D for details. See Appendix D for details. Standard errors are clustered at the recruiter level. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table E.6: Robustness to measurement error in small cells: Effect of tightness in recruiters’ searched occupation on their search behavior in large occupation-canton group cells

	(1)	(2)	(3)	(4)	(5)	(6)
	N contacts	P(DO=1 contact)	E[overlap contact]	P(D=1)	P(contact DO=1)	P(contact)
log(Tightness)	0.6691*** (0.1007)	0.0402*** (0.0088)	-0.3405*** (0.0491)	0.0533*** (0.0057)	0.0145* (0.0083)	0.0233*** (0.0080)
Calendar month FE	X	X	X	X	X	X
Searched occ. x canton scope FE	X	X	X	X	X	X
Recruiter FE	X	X	X	X	X	X
Family	Poisson	OLS	OLS	OLS	OLS	OLS
Observations	1,260,371	109,124	109,124	109,124	104,713	109,124
Mean of dependent var.	1.29655	0.42077	9.33970	0.47002	0.24596	0.28474
Number of recruiters	36,973	23,060	23,060	23,060	22,671	23,060
Pseudo R2 / R2	0.3246	0.4535	0.7504	0.5293	0.4780	0.5165

Notes: This table shows regression estimates based on Equation (3) of the impact of tightness on recruiters’ openness to job seekers with different occupational backgrounds. The sample is restricted to occupation-canton group-cells with at least 30 job seekers every month. The estimates are from Poisson and OLS regressions where each observation represents a unique combination of recruiter, search month, searched occupation, and searched location (i.e., recruiter-month-“cell”). Only combinations with at least one search over the whole sample period are included. The tightness is measured at the monthly level in the searched occupation-location cell, computed as the average daily stock of vacancies divided by the average daily stock of incumbent job seekers. The searched location can be a canton, a combination of cantons, or the whole of Switzerland if no location filter is chosen. See Appendix D for details. Singleton observations are removed. Standard errors are clustered at the recruiter level. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Figure E.3: Effect of tightness on recruiters’ contacts in tight vs slack markets, by occupational wage level



Notes: The figure illustrates the effect of labor market tightness on recruiters’ contact decisions on Job-Room, as predicted by estimates from Equation (3). Panel (a) shows the occupational composition of contacted job seekers. Panel (b) shows the contact rate among job seekers in the result list for movers ($DO = 1$). We differentiate between movers from an occupation with a higher, respectively lower, median wage compared to the searched occupation. The underlying regressions are shown in Appendix Table E.8. The predictions are obtained by holding all control variables constant at their mean effects. “Tight” (“Slack”) refers to predictions at the 90th (10th) percentile of the distribution of labor market tightness. The figure reports the p-values of the coefficient on $\log(Tightness)$ with standard errors clustered at the recruiter-level. See Section 2.1 for the sample description.

Table E.7: Effect of tightness on recruiters' contact patterns by occupation similarity

Dependent Var.:	(1)	(2)	(3)	(4)	(5)	(6)
	P(DO = 1 c.)	P(above median sim. c.)	P(below median sim. c.)	P(c. DO = 1)	P(c. above median sim.)	P(c. below median sim.)
log(Tightness)	0.0480*** (0.0087)	0.0446*** (0.0087)	0.0034 (0.0059)	0.0167*** (0.0058)	0.0217*** (0.0062)	0.0081 (0.0070)
Calendar month FE	X	X	X	X	X	X
Searched occ. x canton scope FE	X	X	X	X	X	X
Recruiter FE	X	X	X	X	X	X
Observations	86,906	86,906	86,906	122,747	122,747	122,747
R2	0.52300	0.50824	0.45292	0.54500	0.51394	0.45907
Mean of dependent var.	0.44227	0.33933	0.10294	0.14191	0.14432	0.13542
Number of recruiters	20,731	20,731	20,731	33,029	33,029	33,029

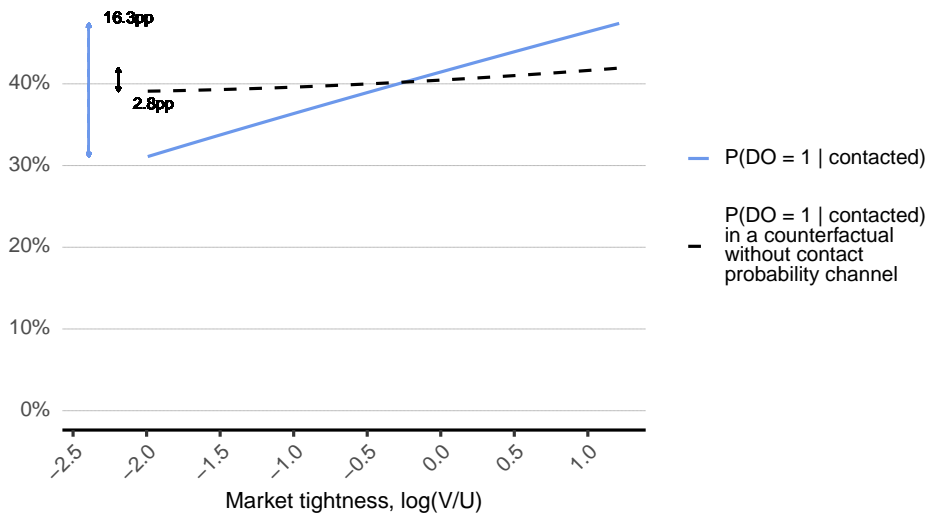
Notes: This table shows OLS regression estimates of the impact of tightness on recruiters' contact patterns across different levels of occupation similarity. Each observation represents a unique combination of recruiter, search month, searched occupation, and searched location (i.e., recruiter-month-“cell”). Columns (1)–(3) show the composition of contacted candidates by occupation similarity, conditional on being contacted. Column (1) shows the share of candidates from the same occupation, (2) the share from above-median similar occupations, and (3) the share from below-median similar occupations. Columns (4)–(6) show contact probabilities by occupation similarity, conditional on being in the result list. Column (4) shows the contact probability for all movers, (5) for movers from above-median similar occupations, and (6) for movers from below-median similar occupations. Above-median (below-median) similar occupations are occupations with above- median (below-median) job requirements overlap with the recruiters' searched occupation. The median is computed among the search results of recruiters and is allowed to vary by searched occupation. The sample is restricted to recruiter-month-cell observations with at least one search result in all three categories. All specifications include calendar month, searched occupation \times canton scope, and recruiter fixed effects. The tightness is measured at the monthly level in the searched occupation-location cell, computed as the average daily stock of vacancies divided by the average daily stock of incumbent job seekers. The searched location can be a canton, a combination of cantons, or the whole of Switzerland if no location filter is chosen. See Appendix D for details. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table E.8: Effect of tightness on recruiters' contact patterns by wage differences

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	P(DO = 1 c.)	P(higher wage c.)	P(lower wage c.)	P(c. DO = 1)	P(c. higher wage)	P(c. lower wage)
log(Tightness)	0.0501*** (0.0087)	-0.0002 (0.0079)	0.0501*** (0.0072)	0.0179*** (0.0060)	0.0141** (0.0069)	0.0207*** (0.0068)
Calendar month FE	X	X	X	X	X	X
Searched occ. x canton scope FE	X	X	X	X	X	X
Recruiter FE	X	X	X	X	X	X
Observations	89,566	89,566	89,566	125,720	125,720	125,720
R2	0.51399	0.50921	0.50067	0.53540	0.47722	0.48327
Mean of dependent var.	0.44298	0.20973	0.23289	0.14693	0.14954	0.14533
Number of recruiters	20,860	20,860	20,860	33,066	33,066	33,066

Notes: This table shows OLS regression estimates of the impact of tightness on recruiters' contact patterns across occupations with different wage levels. Each observation represents a unique combination of recruiter, search month, searched occupation, and searched location (i.e., recruiter-month-“cell”). Columns (1)–(3) show the composition of contacted candidates by wage differences, conditional on being contacted. Column (1) shows the share of candidates from the same occupation, (2) the share from higher-wage occupations, and (3) the share from lower-wage occupations. Columns (4)–(6) show contact probabilities by wage differences, conditional on being in the result list. Column (4) shows the contact probability for all movers, (5) for movers from higher-wage occupations, and (6) for movers from lower-wage occupations. Higher/lower wage classification is based on the median wage of the candidate's last occupation relative to the recruiter's searched occupation. The occupational median values are obtained from the Swiss Earnings Structure Survey in 2018. The sample is restricted to recruiter-month-cell observations with at least one search result in all three categories. All specifications include calendar month, searched occupation \times canton scope, and recruiter fixed effects. The tightness is measured at the monthly level in the searched occupation-location cell, computed as the average daily stock of vacancies divided by the average daily stock of incumbent job seekers. The searched location can be a canton, a combination of cantons, or the whole of Switzerland if no location filter is chosen. See Appendix D for details. Standard errors are clustered at the recruiter level. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Figure E.4: Contact clicks on Job-Room: Decomposition of the total effect of tightness



Notes: The figure illustrates the relationship between labor market tightness and the predicted share of contacts from a different occupation, $P(DO=1|Contacted = 1)$ (solid blue line) in the Job-Room data. It also shows $P(DO=1|Contacted = 1)$ under a counterfactual scenario where the contact rate of movers, $P(Contacted = 1|DO = 1)$, is held constant at its average value for each value of labor market tightness (dashed black line). The predictions hold the effects of all other variables constant at their mean effects. The x-axis ranges from the 10th to the 90th percentile of labor market tightness.

Table E.9: Robustness to zeroes in the tightness measure for tightness, applicant pool composition and application success probability

	P(DO=1)				P(hire DO = x)	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.:	P(DO=1)	P(DO=1)	N DO=0	N DO=1	P(hire DO = x)	P(hire DO = x)
log(Tightness)	0.1720*** (0.0123)	0.2335*** (0.0156)	-0.2102*** (0.0103)	-0.0294*** (0.0073)		
Last worked in different occupation					-0.3206*** (0.0727)	-0.4479*** (0.0818)
Last worked in searched occ. x log(tightness)					-0.0575 (0.0392)	-0.0240 (0.0536)
Last worked in different occ. x log(tightness)					0.1152*** (0.0372)	0.1332*** (0.0459)
Calendar month FE	X	X	X	X	X	X
Firm FE		X	X	X		X
-----	-----	-----	-----	-----	-----	-----
Number of vacancies	96,134	96,134	96,134	96,134	94,410	94,410
Observations	96,124	96,124	96,124	96,124	163,846	163,846
Mean of dependent var.	0.70127	0.70127	0.52139	1.20803	0.01238	0.01238

Notes: This table presents robustness checks using an alternative tightness measure where zeros in vacancy or unemployment counts are replaced with ones before taking logarithms. Estimates in Columns (1) and (2) are from quasibinomial GLM regressions with a logit link. The dependent variable is the share of applicants who last worked in a different occupation. Estimates in Columns (3) and (4) are from a Poisson model. The dependent variable is the number of incumbent applicants ($DO = 0$, Column (3)) and the number of applicants from a different occupation ($DO = 1$, Column (4)). Estimates in Columns (5) and (6) are from logit regressions. The dependent variable is a binary indicator of whether the applicant is hired at the firm that posted the vacancy. The unit of observation is a vacancy posting in Columns (1)–(4) and a vacancy-application combination in Columns (5)–(6). Standard errors clustered at the firm level. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table E.10: Robustness check for tightness, applicant pool composition and application success probability: excluding cells with few vacancies

	P(DO=1)				P(hire DO = x)	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.:	P(DO=1)	P(DO=1)	N DO=0	N DO=1	P(hire DO = x)	P(hire DO = x)
log(Tightness)	0.2952*** (0.0132)	0.3671*** (0.0165)	-0.3203*** (0.0114)	0.0028 (0.0079)		
Last worked in different occupation					-0.2425*** (0.0771)	-0.4197*** (0.0886)
Last worked in searched occ. x log(tightness)					-0.0866 (0.0557)	0.0576 (0.0668)
Last worked in different occ. x log(tightness)					0.1078** (0.0507)	0.1452** (0.0581)
Calendar month FE	X	X	X	X	X	X
Firm FE		X	X	X		X
Number of vacancies	80,544	80,544	80,544	80,544	80,544	80,544
Observations	80,544	80,544	80,544	80,544	133,197	133,197
Mean of dependent var.	0.68797	0.68797	0.52810	1.12562	0.01282	0.01282

Notes: This table presents robustness checks excluding observations from occupation-canton cells with fewer than 30 vacancies. Estimates in Columns (1) and (2) are from quasibinomial GLM regressions with a logit link. The dependent variable is the share of applicants who last worked in a different occupation. Estimates in Columns (3) and (4) are from a Poisson model. The dependent variable is the number of incumbent applicants ($DO = 0$, Column (3)) and the number of applicants from a different occupation ($DO = 1$, Column (4)). Estimates in Columns (5) and (6) are from logit regressions. The dependent variable is a binary indicator of whether the applicant is hired at the firm that posted the vacancy. The unit of observation is a vacancy posting in Columns (1)–(4) and a vacancy-application combination in Columns (5)–(6). Standard errors clustered at the firm level. Statistical significance levels are denoted as *, **, and *** for 10%, 5%, and 1% levels, respectively.