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Search and Matching in Dense Labor Markets: Evidence from Targeted and Realized Occupations of Job Seekers*

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Abstract

This paper examines whether unemployed workers searching in dense urban labor markets are better able to realize their occupational search goals. We use linked employer–employee administrative data from Hungary that record the occupation in which unemployed workers primarily seek work and compare these targets with their subsequent occupations. We find that workers searching in denser labor markets are more likely to find employment in their targeted occupation or in some closely related occupation. These results are robust to a rich set of control variables and alternative specifications. To address potential endogeneity concerns, we use historical data on population and railway infrastructure to construct instruments for contemporary employment density. Finally, examining the role of search targets in post-unemployment occupational mobility, we find that denser labor markets are associated with greater occupational continuity among workers who seek to return to their previous occupation, while those seeking to change occupations tend to move to occupations that are more similar to their previous ones in terms of skill requirements.

Keywords: Labor market density, Occupational targets, Unemployment, Job search, Matching

JEL Codes: J24, J62, J64, R23

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1 Introduction

When workers lose their jobs, they face the difficult choice of what kinds of jobs to target and how long to wait for them. While many workers seek employment in occupations where their skills can be put to productive use, the occupations workers target do not always coincide with those in which they were previously employed.² Some workers may reconsider their occupational choices to correct an earlier poor career choice, pursue higher wages or adjust to changing preferences. Search frictions, however, often make it difficult for workers to find employment in their targeted occupation, leading them to consider jobs in other occupations to avoid prolonged unemployment. While broadening search may facilitate a faster return to employment,³ accepting a job outside the targeted occupation may entail substantial earnings losses upon reemployment, either because skills specific to the preferred occupation are not fully transferable to the new occupation or because workers eventually end up in a lower-paying job. Moreover, accepting work in a less preferred occupation may result in lower job satisfaction and lead workers to continue searching while employed, increasing the likelihood of subsequent job changes or separations. Despite these adverse consequences, relatively little is known about what determines whether unemployed workers are able to find employment in the occupations they prefer. One reason is that administrative and survey data rarely contain information on the occupations in which job seekers are searching for employment.

This paper investigates how local labor market conditions influence workers' ability to realize their search goals. Specifically, we ask whether unemployed workers searching for jobs in dense urban labor markets are better able to find employment in their preferred occupations, or another one that shares similar tasks and skills. The central hypothesis of our paper relies on the basic idea that dense labor markets provide access to a broader and more diverse range of employment opportunities, reducing the costs associated with job search and allowing workers to be more selective about which jobs to pursue and which offers to accept. Accordingly, we expect unemployed workers in dense urban areas to be more likely to end up in their targeted occupation or in a closely related one.

Our hypothesis is situated within the broader theoretical argument that thick labor markets facilitate matching between workers and jobs (Helsley and Strange, 1990; Kim, 1991; Wheeler, 2001; Duranton and Puga, 2004; Gautier and Teulings, 2009; Papageorgiou, 2022). A substantial empirical literature provides evidence consistent with this notion. These studies show that dense labor markets allow for greater worker

²Belot et al. (2019) report that 62 percent of job seekers search in an occupation in which they have prior experience. Using online job search data linked to administrative records from Denmark, Altmann et al. (2023) similarly find that 30 percent of unemployed workers exclusively target occupations in which

³Recent evidence from a field experiment by Belot et al. (2019) suggest that broadening job search to a wider range of occupations increases the number of job interviews, particularly when accompanied by job search advice.

specialization (Garicano and Hubbard, 2007; Jayet and Duranton, 2011; Atalay et al., 2024), improve assortative matching between workers and firms (Andersson et al., 2007; Dauth et al., 2022; Leknes et al., 2022), and reduce the prevalence of skill mismatch (Abel and Deitz, 2015; Corradini et al., 2025). To the best of our knowledge, our paper is the first to examine whether the matching advantages of dense urban labor markets extend to unemployed workers' ability to realize the occupational goals they set at the onset of their search.

Most closely related to our analysis is Bleakley and Lin (2012), who show that workers who experience involuntary job loss in large metropolitan areas are less likely to change occupations and interpret lower occupational mobility as indirect evidence of improved matching in cities. This interpretation, however, implicitly treats remaining in the pre-UE occupation as a favorable search outcome and occupational change as a departure from it. In practice, whether remaining in or leaving the previous occupation represents a successful search outcome depends on the worker's occupational goals. Some workers may seek to return to their previous occupation, while others may actively seek employment in a different one. Occupational mobility can therefore be viewed as the outcome of a two-stage process: unemployed workers first choose which occupation to target and then attempt to find employment in that occupation. Observing workers' occupational targets allows us to distinguish between these two stages and examine whether dense labor markets facilitate job search regardless of whether workers seek to return to their previous occupation or move to a different one.

We use linked employer–employee administrative data from Hungary covering workers registered as unemployed between 2012 and 2015. Our data have several distinct advantages over those typically used in the literature on involuntary occupational mobility following job loss. First, the administrative nature of the data substantially reduces the scope for measurement error in occupational coding, which has been shown to be an important concern in household surveys commonly used to study post-displacement occupational mobility such as the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY). Second, the data provide a much larger sample than is typically available from household surveys. Third, they contain detailed information on workers' employment histories prior to job loss, which allows us to account for differences in previous labor market experience, firm and occupational tenure, and wages that may influence both occupational goals and search outcomes. Finally, and most importantly for our purposes, the dataset records the occupation in which each unemployed worker reports seeking employment at the time of registration. This information allows us to identify workers' stated occupational preferences and directly compare their occupational search targets with their subsequent employment outcomes, which has not been possible in previous studies due to data limitations.

We find a positive relationship between the log employment density of the district in which workers search for jobs and their chances of finding a job in their preferred

occupation. The estimated coefficients are statistically significant and economically meaningful: the difference between the 10th and 90th percentiles of employment density is associated with a 3 percentage point difference in the probability that workers' post-unemployment (post-UE) occupations coincide with their targeted occupation. We further examine the degree of similarity between workers' targeted and post-UE occupations. This allows us to assess whether the benefits of labor market density extend beyond increasing the probability of an exact occupational match and help workers who do not find employment in their targeted occupation obtain jobs that are nevertheless similar to what they initially sought. To construct a continuous measure of similarity across occupations, we use a large-scale survey conducted in 2012 that provides detailed information on the skill requirements of occupations across more than 1,000 firms operating in Hungary. Combining this measure with the administrative data on unemployed workers, we find that post-UE occupations are more similar to workers' targeted occupations in densely populated urban areas. This relationship remains positive when we restrict the sample to workers who find employment outside of their targeted occupation. Moving from the 10th to the 90th percentile of log employment density is associated with an average increase in occupational similarity of approximately one-tenth of a standard deviation.

These results are robust to the inclusion of a rich set of control variables capturing differences in workers' socio-demographic characteristics, employment histories, participation in active labor market programs during the unemployment spell and district-level characteristics. These controls account for systematic differences in the characteristics of workers searching in different local labor markets, as well as differences in local economic conditions that may independently affect job search outcomes. Moreover, the results hold regardless of whether workers seek employment in their pre-UE occupation or not, suggesting that the higher probability of finding a job in the targeted occupation in dense labor markets does not arise from systematic differences in the occupational goals unemployed workers set across labor markets.

We address potential omitted variable bias arising from unobserved locational characteristics, such as amenities or institutional factors related to the effectiveness of local employment services, using an instrumental variable (IV) approach that exploits historical variation in population density and railway connectivity in 1880. In these models, we additionally control for geographic characteristics, historical skill composition, and royal free city status to account for persistent local features that may be correlated with the instruments and independently affect post-UE outcomes. While these specifications produce somewhat smaller coefficient estimates for local employment density, the positive and statistically significant relationship with the probability of being reemployed in the preferred occupation remains qualitatively unchanged.

We next examine the role of occupational targets in the relationship between labor market density and post-unemployment occupational mobility. We find a weak positive relationship between employment density and the probability of returning to the

pre-unemployment occupation, suggesting somewhat lower occupational churning in denser labor markets. This aggregate relationship, however, masks important differences depending on workers' occupational search goals. Among workers who target their pre-unemployment occupation, employment density is positively associated with the probability of returning to that occupation. By contrast, among workers who target a different occupation, we find no systematic relationship between density and the probability of returning to the pre-unemployment occupation, although those who change occupations tend to move to occupations with more similar skill requirements in denser labor markets.

These results provide a different perspective on the relationship between labor market density and occupational mobility documented in previous studies. The lower occupational mobility observed in denser labor markets appears to be primarily associated with workers who actively seek to return to their previous occupation. Workers seeking to change occupations, by contrast, are no more likely to return to the occupation they intend to leave, while their occupational moves tend to involve smaller changes in skill requirements. The relationship between labor market density and occupational mobility therefore depends importantly on workers' search goals. More generally, the matching advantage of dense labor markets may be reflected not simply in whether workers remain in or leave their previous occupation, but also in how closely their subsequent employment corresponds to their occupational choices and skills.

The remainder of the paper is structured as follows. Section 2 describes the data and the variables used throughout the analysis. Section 3 presents our empirical strategy and discusses the main identification and estimation issues. Section 4 presents our main results and examines their robustness to alternative specifications. Section 5 presents our additional results regarding the role of occupational search targets in post-UE occupational mobility. Section 6 concludes.

2 Data and variables

2.1 Data sources

We use the Linked Administrative Panel Database provided by the Databank of the ELTE Centre for Economic and Regional Studies. We rely on the third wave of the dataset (Admin3), which covers a 50 percent random sample of the Hungarian population with a social security number, spanning the period from 2003 to 2017. The dataset is constructed by integrating individual- and firm-level administrative records from multiple government agencies, including the National Health Insurance Fund Management (NEAK), the Hungarian State Treasury (MAK), National Tax and Customs Administration (NAV), National Labor Office (NMH), and the Educational Authority (OH). Structurally, Admin3 consists of a core employment file and several

supplementary modules that can be linked through anonymized identifiers. While the core file contains information on employment status, work hours, and earnings, the supplementary files provide detailed individual- or firm-level information on health care, education, unemployment, and financial data of enterprises.

This dataset is particularly useful for our purposes because it incorporates the unemployment register of the Public Employment Service (PES), which provides detailed information on all individuals who have registered as unemployed. We use data on individuals who entered the unemployment register at least once between 2012 and 2015.^[4] Within this sample, we focus on individuals who were between 25 and 54 years old at the time of registration to avoid differences in search behavior associated with labor market entry and proximity to retirement.^[5] We restrict the analysis to unemployment spells followed by a return to regular employment within 24 months. The 24-month window ensures that individuals entering unemployment throughout our sample period can be observed over a common follow-up period, as ADMIN3 ends in December 2017. Finally, we drop workers who were on recall status during their unemployment spell and subsequently returned to their previous employer. The resulting sample contains 429,448 unemployment spells for 344,703 individuals.^[6]

A unique feature of the PES register is that it includes the occupation in which unemployed workers seek employment. When entering the register, individuals are required to specify this occupation so that local employment offices can provide them with information about vacancies that match their skills and preferences. Throughout the paper, we refer to this occupation as the worker's targeted or preferred occupation. Combining the PES module with the ADMIN3 core employment file allows us to compare workers' targeted occupations with their pre- and post-unemployment occupations. We define the post-unemployment occupation as the occupation held in the first regular job observed after the unemployment spell. The only form of employment that we exclude from our definition of a regular job is public work, as these large-scale programs specifically target unemployed individuals and provide only temporary employment.^[7] Periods spent in public work programs are instead treated as part of unemployment. Accordingly, when a period of public work is observed between two consecutive unemployment spells, we merge the two spells and treat them as a single unemployment spell.

⁴We exclude individuals who registered as unemployed before 2012 because the Hungarian unemployment benefit system underwent several substantial reforms in the preceding years, including two major changes in 2011 alone. For a detailed discussion of these reforms and their effects, see Lindner and Reizer (2020) and Csillag et al. (2023).

⁵In Hungary, unemployed individuals approaching the statutory retirement age could become eligible for a special pre-retirement unemployment benefit, which may substantially alter their incentives to search for and return to regular employment.

⁶Appendix B provides a detailed description of the sample construction process and reports the number of unemployment spells and workers remaining after each restriction.

⁷For a detailed description of the regulation, institutional framework, and implementation of public work programs in Hungary over our study period, see, e.g., Bördös (2015).

We supplement ADMIN3 with data from a unique firm survey that provides detailed information on occupation-specific skill requirements among firms operating in Hungary. We use these data to assess how closely workers' post-unemployment (or realized) occupations are related to their targeted occupations in terms of the skills required. The survey was conducted by the Institute of Economics, Hungarian Academy of Sciences (IE-HAS) in 2012. As part of the survey, firm representatives, typically HR managers and CEOs, were asked to evaluate the educational and skill requirements of up to ten occupations within their establishment. These included the five most common occupations and an additional five randomly selected occupations, or all occupations if fewer than ten were present. For each occupation, respondents assessed the importance of 36 different skills on a five-point scale (1-5). The full list of skills is reported in Appendix A. The resulting data contain 7,342 occupation-specific evaluations collected from 1,029 firms, covering 184 occupations. The survey uses a custom classification of 200 occupations, each constructed by grouping four-digit ISCO codes. To characterize the skill requirements of each occupation, we average the importance ratings across evaluations using survey sampling weights. This results in a 36-dimensional skill vector for each occupation, which we link to the PES data using the corresponding occupation codes.

2.2 Variables

We construct two complementary measures to capture the extent to which unemployed workers realize their occupational search goals. We first consider a binary variable equal to one if the worker's post-unemployment occupation coincides with the occupation targeted at the beginning of the unemployment spell, and zero otherwise. While this measure provides a direct and easily interpretable indicator of whether workers succeed in reaching their stated occupational target, it treats all deviations from the targeted occupation in the same way, regardless of the degree of similarity between the targeted and realized occupations. For example, a worker seeking employment as a confectioner but finding a job as a baker is treated in the same way as one who instead becomes a material handler or a vehicle driver, whereas the former outcome is likely to involve a considerably smaller departure from the worker's occupational target in terms of tasks performed and skills used.

The extent of deviations from the targeted occupation is important because it may have substantial consequences for workers' subsequent labor market outcomes, particularly when the targeted occupation is one in which they have prior experience. A large literature documents that occupational mobility can involve the loss of human capital and is often associated with lower subsequent earnings, especially when workers move to occupations that make limited use of previously acquired skills (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Robinson, 2018; Neffke et al. 2024). This suggests that failing to obtain employment in the exact targeted occupation need not imply

the same economic cost in all cases: being reemployed in closely related occupations may preserve a much larger share of workers' accumulated skills and experience than moves to substantially different occupations. Moreover, smaller deviations from the targeted occupation are likely to be associated with a lower probability of subsequent job separation (Jovanovic, 1979, Dolado et al., 2009).

We therefore complement the binary variable of exact matching with a continuous measure based on the cosine similarity between the skill requirements of workers' targeted and post-UE occupations.⁸ Let $s_{i,j}^T$ and $s_{i,j}^R$ the weighted average importance rating of skill $j \in J$ in worker i 's target and realized occupations respectively. The cosine similarity between these occupations is defined as

$$S_i = \frac{\sum_{j=1}^J s_{i,j}^T s_{i,j}^R}{\sqrt{\sum_{j=1}^J (s_{i,j}^T)^2} \sqrt{\sum_{j=1}^J (s_{i,j}^R)^2}}. \quad (1)$$

This measure defines the degree of similarity between two occupations as the cosine of the angle between their positions in vector space, thereby capturing differences in the relative composition of skill requirements while abstracting from differences in their overall intensity. Given that all occupational skill ratings are non-negative in our data, this measure ranges from 0 to 1 with higher values indicating greater similarity in the skill requirements of the two occupations.

We are primarily interested in whether workers searching in denser labor markets are more likely to realize their occupational search goals. To examine this question, we follow the convention in the urban economics literature (see, e.g. Ciccone and Hall, 1996, Combes et al., 2008) and measure the density of local labor markets by the number of employed workers per square kilometer in the district where the worker is registered as unemployed.⁹ Hungary is divided into 174 districts outside Budapest, corresponding to the LAU-1 (Local Administrative Unit 1) level of the European Union's territorial classification system. Budapest is officially divided into 23 districts; however, we treat the capital as a single local labor market. This results in a total of 175 spatial units in our analysis.

We augment our empirical models with a large set of individual- and district-level characteristics. These variables account for observable differences across unemployed workers and local labor markets that may be related to both employment density and occupational search outcomes. We briefly describe these variables and their sources below, while definitions are provided in Appendix B.

⁸Cosine similarity has been widely used in economics, for example to measure similarity between patents based on their technological content (Jaffe, 1986), examine changes in the industrial composition of regions (Neffke et al., 2018), and, most closely related to our application, similarity in the skill requirements of online job postings (Henning et al., 2026).

⁹The PES register identifies the district in which individuals are registered as unemployed, which may correspond to either their permanent or valid temporary place of residence.

We use data from the PES register to control for basic socio-demographic characteristics, such as gender, age, and educational attainment. We complement this information with workers' employment histories available in the ADMIN3 core file. These variables include labor market experience, tenure with the employer preceding unemployment, occupational tenure in the targeted occupation, and the average monthly wage earned in the last job.

We also account for participation in training programs and public work programs during the unemployment spell, as both may affect workers' search behavior and subsequent occupational outcomes. This information is directly available from the PES unemployment register. Participation in public work may reduce the time and resources devoted to regular job search, whereas training programs may broaden workers' employment opportunities by providing new skills and thereby affect both the direction and success of subsequent job search. The latter is particularly relevant in our setting because targeted occupations are observed only at the beginning of the unemployment spell, and we therefore cannot observe whether workers revise their occupational targets following participation in a training program. Controlling for program participation is also important because exposure to both active labor market programs and public work is systematically related to local labor market conditions, as these programs disproportionately target young and less-educated unemployed workers in disadvantaged, less densely populated areas.

We construct variables capturing the local availability of jobs relevant to each worker's occupational target and the potential competition from other job seekers. The former captures the relative availability of employment opportunities in the worker's targeted occupation, while the latter proxies the intensity of competition for such jobs. We further control for the share of agricultural and manufacturing employment, the share of the public sector in local employment, and unemployment rate to account for differences in local economic structure and labor demand conditions. Finally, in some specifications, we use district-level historical data from 1880 as instruments and additional controls (see details in Section 3).¹⁰

Table 1 presents summary statistics for the full estimation sample and separately for unemployment spells ending in reemployment in the targeted occupation and those ending in reemployment in a different occupation. In the full sample, 23% of unemployment spells end in reemployment in the targeted occupation. Women account for 47% of all spells. In terms of age, 39% of spells involve workers aged 25–34, 37%

¹⁰We do not control for unemployment duration because it may itself be affected by local labor market density, making it a potentially bad control. In particular, unemployment duration may be part of the mechanism through which employment density affects workers' ability to realize their occupational search goals. For example, density may influence workers' willingness to wait for a job that better matches their occupational target rather than accepting a less suitable job. Conditioning on unemployment duration would thus absorb part of the relationship we aim to estimate and could introduce additional bias if duration is correlated by unobserved determinants of our outcome variables, such as innate abilities and motivation.

workers aged 35–44, and 25% workers aged 45–54. Regarding educational attainment, 22% of spells involve workers with elementary education, 65% workers with secondary education, and 12% workers with a college degree. Participation in active labor market programs is relatively limited: training occurs in only 6% of unemployment spells, while 10% involve participation in public work.

There are several notable differences between workers who are reemployed in their targeted occupation and those who take jobs in other occupations. Labor market density differs only slightly across the two groups (4.32 versus 4.35), although the difference is statistically significant. Spells ending in reemployment in the targeted occupation are less likely to involve women (43% versus 49%) and more likely to involve older workers. Educational composition also differs across the two groups. most notably among workers with lower secondary education, who account for 43% of spells ending in reemployment in the targeted occupation but only 30% of those ending in another occupation. The largest differences concern employment histories. Spells ending in reemployment in the targeted occupation involve workers with about 79 months of prior work experience on average, compared with 72 months in the other group, while average occupational tenure is nearly three times as high (39 versus 14 months). The particularly large difference in occupational tenure suggests that stronger attachment to the targeted occupation may be associated with a much greater likelihood of finding reemployment in that occupation. By contrast, previous job tenure and pre-unemployment wages are very similar across the two groups. Participation in training is somewhat more common among spells ending in reemployment outside the targeted occupation (6% versus 4%), suggesting that training participation may be associated with greater occupational mobility rather than with reemployment in the initially targeted occupation.

3 Empirical strategy

We estimate the relationship between local labor market density and workers' ability to realize their occupational search goals using the following specification

$$Y_{id} = \alpha + \beta \log D_{d(i)} + \mathbf{X}_i' \gamma + \mathbf{Z}_{d(i)}' \delta + \varepsilon_{id}. \quad (2)$$

where Y_{id} denotes one of the occupational search outcomes defined in Section 2.2, $D_{d(i)}$ is employment density in district d , $\mathbf{X}_i$ is a vector of individual-level characteristics, $\mathbf{Z}_{d(i)}$ is a vector of district-level characteristics and ε_{id} is an error term. The coefficient of interest is β , which shows how occupational search outcomes vary with local employment density, conditional on the covariates contained in $\mathbf{X}_i$, and $\mathbf{Z}_{d(i)}$. Our hypothesis predicts that workers searching in denser labor markets are more likely to find employment in their targeted occupations and, more generally, to achieve greater skill similarity between their targeted and realized occupations, implying that $\beta > 0$.

A fundamental concern about estimating Eq. (2) using ordinary least squares (OLS) is the potential for bias arising from unobserved factors that are correlated with both local employment density and outcome variables. First, workers may sort across locations based on characteristics that are not fully observed in our data such as innate ability and motivation, that may affect search behavior and subsequent occupational outcomes. To the extent that workers with higher levels of unobserved ability are disproportionately concentrated in large urban areas, the estimated coefficient on employment density may partly reflect differences in worker ability rather than the effect of labor market density itself. Recent empirical evidence suggests that sorting on unobserved worker characteristics can account for part of the observed differences in various job search outcomes across cities (Moretti and Yi, 2024).¹¹

A second potential source of bias arises from unobserved differences in the effectiveness of local employment offices and other institutional characteristics that may affect job search outcomes. Policy evaluations of the unemployment profiling system in Hungary point to substantial differences across districts in the capacity and operation of local employment offices (Bördös et al., 2018). In particular, caseloads per caseworker vary considerably across districts, while administrative and regulatory duties often leave caseworkers with limited capacity to provide individualized assistance, assess job seekers' needs, or develop personalized action plans. These constraints appear to be more pronounced in less urbanized districts, potentially leading to an upward bias in the estimated coefficient on employment density.

To address endogeneity concerns, we follow the empirical literature on agglomeration economies and instrument contemporary employment density using census data on the spatial distribution of population and railway accessibility in 1880. The validity of these instruments requires that, conditional on exogenous covariates, historical population patterns and railway accessibility affect the probability of finding employment in the targeted or a similar occupation only through their persistent influence on contemporary employment density. The most important concern with historical instruments of this kind is that the factors determining the spatial distribution of economic activity in the past may themselves be persistent and continue to affect present-day labor

¹¹A common approach to addressing spatial sorting on unobserved worker characteristics is to include worker fixed effects in the model. In our setting, however, this approach is not without problems. Identification would come exclusively from individuals who experience multiple unemployment spells and move across districts between these spells. This raises several concerns. First, these individuals are unlikely to constitute a random sample of the unemployed population. Estimates based on this group may therefore not be representative of the broader population of unemployed workers. Second, worker fixed effects account only for time-invariant unobserved heterogeneity and do not address the potential endogeneity of geographic mobility itself. In particular, workers who have difficulty finding suitable employment in their current local labor market may be more likely to relocate to denser areas with better employment opportunities. In this case, changes in local employment density partly reflect previous search outcomes, violating the strict exogeneity assumption required for fixed-effects estimation. Finally, these individuals represent only a small fraction of our sample (12,056 out of 344,703, or approximately 3.5 percent), leaving relatively little within-worker variation in local employment density and thus substantially reducing the precision of the estimates.

market outcomes (Combes and Gobillon, 2015). In particular, historical population concentration may reflect persistent differences in human capital, institutions, and the spatial sorting of workers (Nunn, 2009).

We augment our 2SLS specifications with several variables capturing historical differences in human capital and institutional quality. First, we control for the literacy rate in 1880, which provides a direct measure of differences in the local stock of human capital at the time. Second, we include the share of Protestants in the population in 1880. Historical evidence suggests that Protestant populations tended to have higher levels of education and literacy, which contributed to the greater economic prosperity of predominantly Protestant areas (Becker and Woessmann, 2009).¹² Finally, we control for royal free city status in 1871. Royal free cities enjoyed extensive privileges and a greater degree of self-government, providing them with institutional and commercial advantages that may have contributed to their early development and generated persistent differences relative to other locations. We therefore construct an indicator equal to one for districts containing a settlement that held royal free city status and zero otherwise. Together, these controls should mitigate concerns that the spatial distribution of population and railway infrastructure in 1880 is correlated with persistent differences in human capital and institutions.

Beyond omitted variables, a further concern is spatial dependence across local labor markets. Although districts provide a reasonable approximation of local labor markets and commuting patterns in most parts of Hungary, their administrative boundaries do not perfectly coincide with the geographic scope of workers' job search. Employment opportunities in neighboring districts may also affect workers' ability to find a suitable job by expanding the set of jobs accessible through commuting. If employment density in neighboring districts independently improves workers' prospects of finding a job in their targeted occupation, omitting it from the model would attribute part of this neighboring-market effect to the worker's own district, potentially leading to an upward bias in the estimated coefficient on local employment density. To account for this possibility, we augment Eq. (2) with a spatial lag of employment density.

Finally, since employment density varies at the district level while our outcomes are measured at the individual level, observations within the same district may be subject to correlated errors. Ignoring this within-district correlation may lead to underestimated standard errors (Moulton, 1990). We therefore cluster standard errors at the district level in all specifications.

¹²Koster and Ozgen (2021) adopt a similar approach, instrumenting contemporary employment density with its historical distribution in 1909 while additionally controlling for the historical skill composition of local employment to account for persistent spatial sorting on skills.

4 Results

4.1 Baseline results

We begin our empirical investigation by estimating Eq. (2) for our first outcome, a binary variable equal to one if the post-UE occupation coincides with the occupation targeted at the beginning of the unemployment spell. Table 2 reports the estimates from specifications with different sets of control variables. The baseline specification in column (1) establishes the relationship between local employment density and the probability of finding a job in the targeted occupation, controlling only for the year of registration. To facilitate the interpretation of the estimated coefficient, we express its magnitude in terms of the difference in log employment density between districts at the 10th and 90th percentiles of the distribution of employment density.¹³ The 90–10 percentile difference in log employment density is associated with a 4.7 percentage point difference in the probability of finding employment in the targeted occupation. To put this magnitude into perspective, the estimated difference corresponds to approximately 0.11 standard deviations of the dependent variable.

Column (2) adds targeted occupation fixed effects. Accounting for the targeted occupation is important because occupations are not randomly distributed across local labor markets. Less common occupations, particularly those requiring higher levels of education and more complex skills, tend to be disproportionately concentrated in larger urban areas (Gautier and Teulings, 2009; Atalay et al. 2024). At the same time, job seekers targeting such occupations may generally face a lower probability of finding employment in exactly the occupation they seek. Differences in the composition of occupational targets may therefore partly account for the observed relationship between employment density and target realization. Once targeted occupation fixed effects are included, the estimated coefficient decreases from 0.0109 to 0.0078, suggesting that differences in the composition of occupational targets account for part of the unconditional relationship between employment density and the binary outcome.

Columns (3) and (4) further control for workers' socio-demographic characteristics and employment histories, which account for observable differences in worker composition across local labor markets that may be related to both residential sorting and job search outcomes. The estimated coefficient declines only moderately, from 0.0078 to 0.0062, and remains statistically significant at the 1 percent level. In column (5), we additionally account for workers' participation in training and public work programs during the unemployment spell. This is particularly important in the Hungarian context, where participation in these programs is systematically related to local labor market conditions and is more common in disadvantaged, less densely populated areas. The estimated

¹³This difference is roughly equivalent to the difference between Vasvári district, a relatively sparsely populated area in western Hungary, and Győri district, centered around Győr, the sixth-largest city in Hungary.

coefficient decreases further, to 0.0057, but remains highly statistically significant.

Finally, column (6) adds local labor market characteristics, including the share of local employment in the targeted occupation, the share of registered job seekers targeting the same occupation, and other characteristics of the district. The first two variables are particularly important for distinguishing the relationship with overall employment density from differences in the local composition of employment opportunities and competition from other job seekers searching for similar jobs. The estimated coefficient increases somewhat following the inclusion of these controls, from 0.0057 to 0.0070. In this specification, the 90–10 percentile difference in log employment density is associated with a 3.0 percentage point difference in the probability of finding employment in the targeted occupation, corresponding to approximately 0.07 standard deviations of the dependent variable.

Table 3 turns to the skill similarity of targeted and realized occupations. Panel A reports the results for the full sample. The estimated coefficient on log employment density is positive and statistically significant across all specifications and decreases only moderately as additional controls are introduced. With all control variables included, the coefficient is 0.0032, indicating that workers searching in denser labor markets tend to find employment in occupations with skill requirements that more closely resemble those of their initial targets.

An important question is whether this relationship simply reflects the higher probability of exact occupational matches in denser labor markets documented in Table 2. Since targeted and realized occupations have identical skill vectors whenever workers find employment in exactly the occupation they target, a higher incidence of exact matches mechanically increases average skill similarity. To examine whether this relationship also holds when targeted and realized occupations differ, Panel B restricts the sample to workers who are reemployed in an occupation different from the one they initially targeted. The results continue to show a positive and statistically significant relationship between employment density and skill similarity. Although the estimated coefficient declines considerably after targeted occupation fixed effects are introduced, it remains remarkably stable across specifications. In column 6, the coefficient on log employment density is 0.0020 and remains statistically significant at the 1 percent level. Thus, the positive relationship between density and skill similarity in the full sample is not driven solely by the greater prevalence of exact occupational matches in denser labor markets. Even among workers who do not find employment in the occupation they initially target, those searching in denser labor markets tend to obtain jobs with skill requirements that are more similar to their occupational targets.

The magnitudes are also economically meaningful. Based on the parameter estimates reported in column 6, the 90–10 percentile difference in log employment density is associated with differences in skill similarity of approximately 0.11 standard deviations in the full sample and 0.10 standard deviations among workers reemployed outside

their targeted occupation.

2. Robustness

The results presented in the previous section indicate a positive relationship between local employment density and workers' ability to find employment in their targeted occupations or in some closely related occupation. However, one may argue that employment density is correlated with unobserved individual and locational characteristics so that coefficient β in Eq 2 it may not solely capture the effect of labor market density on job search outcomes. To address these concerns, we complement our OLS estimates with 2SLS specifications that use historical measures of population density and railway accessibility as instruments for contemporary employment density.

Table 4 reports the results of the 2SLS specifications. In addition to the controls used in the baseline specifications, all models include historical controls for literacy, the share of Protestants in the population, and royal free city status. As discussed in Section 3, these variables are intended to account for historical differences in human capital and local institutions that may have influenced the spatial distribution of population and transport infrastructure in the late nineteenth century and generated persistent differences across locations.

Turning first to instrument strength, historical population density is strongly related to contemporary employment density, with Kleibergen–Paap F-statistics well above conventional thresholds in all specifications. However, the first-stage relationship is considerably weaker for historical railway accessibility. When the railway connection indicator is used as the only excluded instrument, the Kleibergen–Paap F-statistic ranges between approximately 13 and 17, raising some concern about potential weak-instrument problems. When both historical variables are used jointly, however, the corresponding F-statistics are close to or above 300.

With regard to the parameter estimates, the 2SLS results are broadly consistent with those obtained from the baseline specifications. Columns (1)–(3) report the estimates for the probability of finding employment in the targeted occupation. The coefficient on employment density is positive and statistically significant across all three instrument sets, although the estimated magnitudes are somewhat smaller than the corresponding OLS estimate. Depending on the instrument set, the 90–10 percentile difference in log employment density is associated with a 2.6–3.4 percentage point difference in the probability of finding employment in the targeted occupation.

Columns (4)–(6) report the estimates for the skill similarity between targeted and realized occupations in the full sample. The results show a similar pattern: the coefficients remain positive and statistically significant across all specifications. Finally, columns (7)–(9) restrict the sample to workers who find employment outside their targeted occupation. The estimated relationship remains positive in this subsample,

although the coefficients are smaller. Depending on the instrument set, the coefficients are statistically significant at the 5 or 10 percent level.

The second concern regarding our estimates is spatial dependence arising from a potential mismatch between the delineation of administrative districts and the geographic scope of workers' job search and commuting. Employment opportunities are not necessarily confined to the district in which a worker is registered as unemployed, as unemployed workers may also search for and accept jobs in neighboring districts. As a result, employment density in adjacent districts may independently affect occupational search outcomes and, because employment density tends to be spatially correlated, omitting these neighboring labor market conditions could lead to an upward bias in the estimated coefficient on own-district employment density.

Table 5 reports estimates from specifications that augment our baseline models with a spatial lag of employment density. Compared with column 6 of Tables 2 and 3, the estimated coefficients on own-district employment density remain virtually unchanged. Moreover, the coefficient on spatially lagged employment density is not statistically different from zero for either outcome or sample. These results provide no evidence that employment opportunities in neighboring districts independently affect workers' ability to find employment in their targeted occupation or in occupations with similar skill requirements. They also suggest that the positive relationship between own-district employment density and occupational search outcomes is unlikely to be driven by spatial dependence in employment density across neighboring districts.

In Appendix C we present several additional sensitivity checks. First, we consider alternative reemployment windows of 6, 12, and 18 months instead of the 24-month window used in the baseline analysis. Second, we re-estimate our main specifications using alternative sample definitions. We restrict the analysis to workers' first observed unemployment spells and to workers experiencing only a single unemployment spell. Finally, we include workers who return to their previous employer. While some of these restrictions affect the magnitude of the estimated coefficients, the qualitative pattern of the results remains unchanged and none of these alternative specifications materially affects our main conclusions.

5 Post-unemployment occupational mobility

The analysis so far has focused on whether workers are able to find employment in or close to the occupations they target. We now turn to the implications of occupational targets for interpreting post-unemployment occupational mobility. Previous studies typically assess occupational mobility by comparing workers' pre- and post-unemployment occupations, with lower mobility in denser labor markets interpreted as evidence consistent with more efficient matching (Bleakley and Lin, 2012; Maré et al., 2023).

Such an interpretation, however, does not take into account whether workers intend to remain in their previous occupation or move to a different one. Returning to the previous occupation may represent a successful search outcome for a worker who intends to remain in that occupation, but not for someone who actively seeks to change occupations. Observing workers' occupational targets allows us to distinguish between these cases and examine whether the relationship between employment density and post-unemployment occupational mobility differs according to workers' stated search goals.

To assess the role of occupational targets in post-unemployment occupational mobility, we replace the outcomes in Eq. (2) with two measures comparing workers' pre- and post-unemployment occupations. The first is an indicator equal to one if a worker returns to their pre-unemployment occupation, while the second measures the similarity between the skill requirements of their pre- and post-unemployment occupations. We estimate these models first for the full sample and then separately for workers who target their pre-unemployment occupation and those who seek employment in a different occupation.

Table 6 reports the results. Columns (1)–(3) examine the probability of returning to the pre-unemployment occupation. In the full sample (column 1), employment density is positively associated with returning to the previous occupation. The 90–10 percentile difference in log employment density is associated with a 1.4 percentage point higher probability of returning to the pre-unemployment occupation, corresponding to approximately 0.03 standard deviations of the dependent variable. This result is consistent with previous evidence that workers in denser labor markets are less likely to change occupations following job loss.

Splitting the sample according to workers' occupational targets reveals substantial differences behind this aggregate relationship. Among workers who target their pre-unemployment occupation, the estimated coefficient is positive and more than twice as large as in the full sample (column 2). Thus, workers who seek to return to their previous occupation are more likely to succeed in doing so when searching in denser labor markets. Among workers who target a different occupation, by contrast, the estimated coefficient is considerably smaller and not statistically significant (column 3).

Columns (4)–(6) present estimates from models in which the dependent variable is the skill similarity between workers' pre- and post-unemployment occupations. In the full sample (column 4), employment density is positively associated with occupational similarity. The 90–10 percentile difference in log employment density is associated with a 0.0064 increase in cosine similarity, equivalent to approximately 0.05 standard deviations of the similarity measure. The positive relationship remains when the sample is split according to workers' occupational targets. Among job seekers targeting their pre-unemployment occupation, greater density is associated with higher skill similarity between their pre- and post-unemployment occupations, consistent with the binary

results in columns (1)–(3). More interestingly, the relationship is also positive and statistically significant among workers who target a different occupation. Thus, although workers seeking to change occupations are no more likely to return to their previous occupation in denser labor markets, the occupations in which they subsequently find employment tend to have skill requirements that are more similar to those of their previous occupation.

Taken together, these results provide a more nuanced interpretation of the relationship between labor market density and occupational mobility. The lower prevalence of occupational switching in denser labor markets appears to be largely driven by workers who seek to return to their previous occupation. Among workers who instead seek to change occupations, density is not associated with a greater likelihood of returning to the previous occupation, while their subsequent occupations tend to be more similar to their previous ones in terms of skill requirements. These findings suggest that the matching advantages of dense labor markets cannot be fully captured by occupational mobility alone. A successful match may involve returning to the previous occupation for workers who wish to stay, but it may equally involve moving to a different occupation for those seeking change, while allowing them to retain more of the value of their previously acquired skills.

6 Conclusions

This paper studies whether unemployed workers searching in dense urban labor markets are better able to realize their occupational search goals. While a large literature emphasizes that matching between workers and jobs is more efficient in large urban areas, relatively little is known about whether these advantages help unemployed workers find the types of jobs they actually seek. We address this question using linked administrative data from Hungary that record workers' targeted occupations at the time of registration as unemployed. This information allows us to compare workers' stated occupational search goals with the jobs they subsequently obtain.

Our results show that workers searching in denser labor markets are more likely to find employment in the occupation they initially target. Moreover, even workers who do not find employment in their targeted occupation are more likely to obtain jobs with similar skill requirements when searching in denser labor markets. Consistent with earlier work, we also find that unemployed workers in dense urban areas are somewhat less likely to change occupations after job loss. This aggregate relationship, however, masks substantial differences according to workers' search goals. Among job seekers who target their previous occupation, density is positively associated with the probability of returning to that occupation. By contrast, among those who target a different occupation, density is not associated with a greater probability of returning to the pre-unemployment occupation, although their post-unemployment occupations

tend to be more similar to their previous ones in terms of skill requirements. Thus, the lower prevalence of occupational switching in denser labor markets appears to be largely driven by workers who actively seek to return to their previous occupation. More generally, these results highlight the importance of workers' search goals for interpreting post-unemployment occupational mobility: lower occupational mobility does not necessarily indicate better matching, but may do so when it reflects workers' ability to return to an occupation in which they actively seek employment.

These results also have implications for employment policy. Workers searching in sparsely populated areas with limited employment opportunities appear to face a disadvantage that extends beyond the time required to find a job: they may also have greater difficulty finding employment that corresponds to their skills and preferences. Such mismatches may entail losses of occupation-specific human capital and have adverse consequences for subsequent earnings and employment stability. Employment policies targeted at areas with particularly limited local opportunities should therefore seek to broaden the range of jobs accessible to unemployed workers. Our results also suggest that the geographic scope of workers' job search may be relatively limited, as employment density in neighboring districts is not systematically associated with either the probability of finding employment in the targeted occupation or the similarity between targeted and realized occupations. Improving transport links and commuting opportunities may therefore help expand the set of employment opportunities accessible to workers without requiring them to relocate.

Training programs and job-search assistance may also help workers adapt their skills and broaden their feasible occupational choices when suitable local vacancies are scarce. More generally, our results suggest that place-based employment policies targeted at sparsely populated areas should be evaluated not only by whether they accelerate reemployment, but also by whether they enable workers to obtain jobs that make productive use of their skills and correspond more closely to their preferences.

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Table 1 Summary statistics by reemployment in the targeted occupation

	Entire Sample		Reemployed in targeted occupation		Reemployed in different occupation	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Dependent variables						
Reemployed in targeted occupation (yes=1)	0.23	0.42	1.00	0.00		0.00
Skill similarity: targeted and realized occupations	0.80	0.13	1.00	0.00	0.75	0.09
Independent variables						
Log employment density	4.34	1.33	4.32	1.31	4.35	1.33
Female (=1)	0.47	0.50	0.43	0.50	0.49	0.50
Age (25-34 ys)	0.39	0.49	0.34	0.47	0.40	0.49
Age (35-44 ys)	0.37	0.48	0.38	0.49	0.36	0.48
Age (45-54 ys)	0.25	0.43	0.28	0.45	0.23	0.42
Education - elementary (=1)	0.22	0.42	0.20	0.40	0.23	0.42
Education - lower secondary (=1)	0.33	0.47	0.43	0.50	0.30	0.46
Education - upper secondary (=1)	0.32	0.47	0.27	0.44	0.34	0.47
Education - tertiary (=1)	0.12	0.33	0.10	0.30	0.13	0.34
Participate in training program (=1)	0.06	0.23	0.04	0.20	0.06	0.24
Participate in public work (=1)	0.10	0.30	0.07	0.26	0.11	0.32
Labor market experience (in month)	73.54	38.74	79.45	36.86	71.76	39.11
Occupational tenure (in month)	20.07	32.48	39.21	39.67	14.32	27.48
Job tenure (in month)	18.55	28.38	19.71	29.03	18.20	28.17
Log of monthly wage in pre-UE job (HUF)	11.38	1.14	11.39	1.09	11.38	1.16
Share of employment in targeted occupation	0.06	0.07	0.06	0.07	0.06	0.08
Share of job seekers targeting the same occupation	0.05	0.06	0.05		0.05	0.06
Share of agricultural employment	0.05	0.04	0.05	0.04	0.05	0.04
Share of manufacturing employment	0.29	0.09	0.29	0.09	0.29	0.09
Share of public sector employment	0.24	0.05	0.24	0.05	0.24	0.05
Unemployment rate	0.13	0.04	0.13	0.04	0.13	0.04
Instruments						
Log population density in 1880	4.39	0.95	4.38	0.94	4.40	0.96
Railway connections in 1880 (yes=1)	0.75	0.43	0.75	0.43	0.75	0.44
Number of observations (UE spells)	429,448		79,978		349,470	

Table 2 Probability of finding a job in the targeted occupation

Dependent variable: Reemployed in targeted occupation						
	(1)	(2)	(3)	(4)	(5)	(6)
Parameter estimates of log density	0.0109*** (0.00070)	0.0078*** (0.00064)	0.0075*** (0.00059)	0.0062*** (0.00048)	0.0057*** (0.00049)	0.0070*** (0.00054)
Est. diff. in probability associated with p90–p10 diff. in log density	0.0465*** (0.00298)	0.0329*** (0.00272)	0.0316*** (0.00251)	0.0263*** (0.00201)	0.0242*** (0.00206)	0.0297*** (0.00228)
Est. diff. in SD units	0.1101	0.0781	0.0749	0.0624	0.0574	0.0706
Adj R-squared	0.002	0.076	0.078	0.128	0.129	
Targeted occupation FE	No	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Employment history	No	No	No	Yes	Yes	Yes
Participation in training and public work	No	No	No	No	Yes	Yes
Local labor market characteristics	No	No	No	No	No	Yes

Notes: Each column presents the results of a separate regression estimated by OLS. The dependent variable is an indicator equal to one if the post-unemployment occupation coincides with the targeted occupation and zero otherwise. All regressions include a constant and dummies for the year of registration. Individual characteristics include a female dummy, age-group and education dummies. Employment history includes labor market experience, tenure in the job preceding unemployment, and the log of average monthly wage in that job. Local labor market characteristics include the unemployment rate, the sectoral composition of local employment, the share of local employment in the targeted occupation and the share of job seekers with the same occupational target. Standard errors clustered at the district level are reported in parentheses. The number of observations is 429,448. *** $p < 0.01$

Table 3 Skill similarity between the targeted and post-UE occupations

Dependent variable: Skill similarity between targeted and realized occupation						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
Parameter estimates of log density	0.0044*** (0.00037)	0.0042*** (0.00041)	0.0039*** (0.00033)	0.0036*** (0.00026)	0.0033*** (0.00025)	0.0032*** (0.00038)
Est. diff. in similarity associated with p90–p10 diff. in log density	0.0188*** (0.0015)	0.0176*** (0.0017)	0.0165*** (0.0014)	0.0154*** (0.0011)	0.0141***	0.0137*** (0.0016)
Est. diff. in SD units	0.143	0.135	0.126	0.118	0.107	0.105
Adj R-squared	0.010	0.094	0.099	0.148	0.149	0.151
Panel B: Reemployed in different occupation						
Parameter estimates of log density	0.00657*** (0.00039)	0.00310*** (0.00028)	0.00285*** (0.00021)	0.00268*** (0.00020)	0.00262***	0.00199*** (0.00029)
Est. diff. in similarity associated with p90–p10 diff. in log density	0.0279*** (0.0016)	0.0132*** (0.0011)	0.0121***	0.0114*** (0.0010)	0.0111***	0.0084*** (0.0013)
Est. diff. in SD units	0.324	0.153	0.141	0.132	0.129	0.098
Adj R-squared	0.01	0.162	0.179	0.182		0.187
Targeted occupation FE	No	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Employment history	No	No	No	Yes	Yes	Yes
Participation in training and public work	No	No	No	No	Yes	Yes
Local labor market characteristics	No	No	No	No	No	Yes

Notes: Each column within each panel presents the results of a separate regression estimated by OLS. The dependent variable is the cosine similarity between the skill vectors of the targeted and post-UE occupations. All regressions include a constant and dummies for the year of registration. For a description of the control variables, see the notes to Table 2. Standard errors clustered at the district level are reported in parentheses. The number of observations is 429,448 in Panels A and 349,470 in Panel B. *** $p < 0.01$

Table 4 Endogeneity of log employment density

Dependent variable	Reemployed in targeted occupation			Skill similarity between targeted and realized occupations					
Sample	Full sample			Full sample			Reemployed in different occupation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parameter estimates of log density	0.0062*** (0.0014)	0.0084*** (0.0014)	0.0063*** (0.0014)	0.0021** (0.0007)	0.0031** (0.0014)	0.0021** (0.0008)	0.0009* (0.0005)	0.0015** (0.0007)	0.0009** (0.0004)
Est. diff. in outcome associated with p90–p10 diff. in log density	0.0264*** (0.0061)	0.0343*** (0.0011)	0.0266*** (0.0061)	0.0089** (0.0032)	0.0132** (0.0062)	0.00910** (0.0033)	0.0041* (0.0021)	0.0067** (0.0041)	0.0041** (0.0021)
Est. diff. in SD units	0.062	0.042	0.063	0.069	0.053	0.069	0.047	0.078	0.048
Excluded instrument	Log pop density, 1880	Railway, 1880	Log pop density 1880 + Railway, 1880	Log pop density, 1880	Railway, 1880	Log pop density 1880 + Railway, 1880	Log pop density 1880	Railway, 1880	Log pop density 1880 + Railway, 1880
Target occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employment history	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local labor market characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Historical controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	583.53	16.60	293.59	612.53	12.60	305.87	570.32	12.96	287.93
Number of observations	429,448	429,448	429,448	429,448	429,448	429,448	349,470	349,470	349,470

Notes: Each column presents the results of a separate regression estimated by 2SLS. All regressions include a constant and dummies for the year of registration. We use the log of population density in 1880 and a dummy for railway connections as instruments. For a description of the control variables, see the notes to Table 2. Historical controls include the share of literate population in 1880, the share of Protestants in 1880, and a dummy for royal free city status. Standard errors clustered at the district level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 5 Spatial dependence in log employment density

Dependent variable	Reemployed in targeted occupation	Skill similarity between targeted and realized occupations	
Sample	Full sample	Full sample	Reemployed in different occupation
	(1)	(2)	(3)
Log density	0.0070*** (0.0004)	0.0030*** (0.0004)	0.0020*** (0.0003)
Spatial lagged log density	0.0004 (0.0013)	-0.0007 (0.0006)	0.0001 (0.0005)
Adj R-squared	0.129	0.151	0.187
Targeted occupation FE	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes
Employment history	Yes	Yes	Yes
Participation in training and public work	Yes	Yes	Yes
Local labor market characteristics	Yes	Yes	Yes

Notes: Each column presents the results of a separate regression estimated by OLS. All regressions include a constant and dummies for the year of registration. For a description of the control variables, see the notes to Table 2. The spatial lag of log employment density is calculated using a spatial weights matrix based on rook contiguity. Standard errors clustered at the district level are reported in parentheses. The number of observations is 429,448. *** $p < 0.01$

Table 6 Occupational mobility

Dependent variable	Reemployed in pre-UE occupation			Skill similarity between pre-UE and post-UE occupations		
Sample	Full sample	Targets pre-UE occupation	Targets different occupation	Full sample	Targets pre-UE occupation	Targets different occupation
	(1)	(2)	(3)	(4)	(5)	(6)
Parameter estimates of log density	0.0032** (0.0014)	0.0068*** (0.0013)	0.0018 (0.0014)	0.0015*** (0.0003)	0.0019*** (0.0003)	0.0014*** (0.0000)
Est. diff. in the dep. var. associated with p90–p10 diff. in log density	0.0139** (0.0014)	0.0287*** (0.0059)	0.0077 (0.0060)	0.0064*** (0.0013)	0.0081*** (0.0016)	0.0062*** (0.0015)
Est. diff. in SD units	0.031	0.058	0.019	0.046	0.058	0.046
Standard deviation of dep. var.	0.444	0.498	0.396	0.138	0.140	0.133
Number of observations	429,448	429,448	429,448	429,448	429,448	429,448
Adj R-squared	0.088	0.089	0.079	0.108	0.112	0.102
Pre-UE occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Employment history	Yes	Yes	Yes	Yes	Yes	Yes
Participation in training and public work	Yes	Yes	Yes	Yes	Yes	Yes
Local labor market characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column presents the results of a separate regression estimated by OLS. The dependent variable is an indicator equal to one if the post-unemployment occupation coincides with the pre-UE occupation and zero otherwise. All regressions include a constant and dummies for the year of registration. For a description of the control variables, see the notes to Table 2. Standard errors clustered at the district level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$

Appendix A – Skill Definitions

This section presents the complete list and brief descriptions of the skills included in the IE-HAS Skill Survey. The classification of skills closely follows that of the O*NET database, which distinguishes between 10 basic and 25 cross-functional skills. Basic skills refer to functional abilities that facilitate the acquisition of knowledge and the processing of information, whereas cross-functional skills comprise more general capabilities that facilitate the performance of activities common to a wide range of jobs. Compared with the O*NET classification, the IE-HAS Skill Survey includes one additional skill measuring the importance of user-level computer proficiency.

Reading Comprehension — Understanding written sentences and paragraphs in work-related documents.

Active Listening — Giving full attention to what other people are saying and taking time to understand the points being made.

Writing — Communicating effectively in writing as appropriate for the needs of the audience.

Speaking — Talking to others to convey information effectively.

Mathematics — Using mathematics to solve problems.

Science — Using scientific rules and methods to solve problems.

Critical Thinking — Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems.

Active Learning — Understanding the implications of new information for current and future problem-solving and decision-making.

Learning Strategies — Selecting and using appropriate training or instructional methods and procedures when learning or teaching new things.

Monitoring — Monitoring and assessing the performance of oneself, other individuals, or organizations to make improvements or take corrective action.

Social Perceptiveness — Being aware of others' reactions and understanding why they react as they do.

Coordination — Adjusting actions in relation to others' actions.

Persuasion — Persuading others to change their minds or behavior.

Negotiation — Bringing others together and trying to reconcile differences.

Instructing — Teaching others how to do something.

Service Orientation — Actively looking for ways to help people.

Complex Problem Solving — Identifying complex problems and reviewing related

information to develop and evaluate options and implement solutions.

Operations Analysis — Analyzing needs and product requirements to create a design.

Technology Design — Generating or adapting equipment and technology to serve user needs.

Equipment Selection — Determining the kind of tools and equipment needed to do a job.

Installation — Installing equipment, machines, wiring, or programs to meet specifications.

Programming — Writing computer programs for various purposes.

Operation Monitoring — Watching gauges, dials, or other indicators to make sure a machine is working properly.

Operation and Control — Controlling operations of equipment or systems.

Equipment Maintenance — Performing routine maintenance on equipment and determining when and what kind of maintenance is needed.

Troubleshooting — Determining causes of operating errors and deciding what to do about them.

Repairing — Repairing machines or systems using the needed tools.

Quality Control Analysis — Conducting tests and inspections of products, services, or processes to evaluate quality or performance.

Judgment and Decision Making — Considering the relative costs and benefits of potential actions to choose the most appropriate one.

Systems Analysis — Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.

Systems Evaluation — Identifying measures or indicators of system performance and the actions needed to improve or correct performance relative to the goals of the system.

Time Management — Managing one's own time and the time of others.

Management of Financial Resources — Determining how money will be spent to get the work done and accounting for these expenditures.

Management of Material Resources — Obtaining and ensuring the appropriate use of equipment, facilities, and materials needed to do certain work.

Management of Personnel Resources — Motivating, developing, and directing people as they work and identifying the best people for the job.

Additional skill

Computer Skills — Using word-processing software, email, the internet, and other

office applications to perform routine tasks.

Appendix B – Sample Construction and Variable Definitions

Sample construction

Table B1 summarizes the construction of our estimation sample. We begin with workers aged 25–54 who registered as unemployed between 2012 and 2015, comprising 513,946 unemployment spells involving 397,584 individuals. We focus on this age group to obtain a sample of workers with relatively strong labor market attachment. Younger job seekers include a relatively large share of low-educated workers with little or no previous labor market experience, for whom occupational targets may reflect initial career choices rather than post-employment job search. Older workers are excluded because special pre-retirement benefits available during the period under study may have affected their incentives to search for and return to employment.

We further restrict the sample to workers who return to employment within 24 months of registration. As occupational targets are observed only at the beginning of the unemployment spell, their relevance for subsequent job search is likely to diminish as the spell progresses. This restriction leaves 450,459 unemployment spells involving 345,741 workers.

Finally, we exclude workers who return to their previous employer after unemployment. Such recalls need not represent a new matching process, as the unemployment spell may reflect a temporary interruption of an existing employment relationship and workers may anticipate returning to their former employer. Their search behavior and occupational outcomes may therefore differ from those of workers searching for a new employer. After applying this restriction, our final estimation sample contains 429,448 unemployment spells involving 344,703 workers.

Dependent variables

Reemployed in targeted occupation — Dummy variable equal to 1 if the occupation of the worker's post-unemployment job coincides with the occupation targeted at the time of registration, and 0 otherwise. The targeted occupation is the occupation reported by the job seeker at registration as the occupation in which they are primarily seeking employment.

Skill similarity between targeted and realized occupations — Cosine similarity between the skill-requirement vectors of the targeted occupation and the first occupation obtained after unemployment, defined as in Equation (1). Higher values indicate greater similarity in the relative composition of skill requirements between the two occupations.

Independent variables

Log employment density — Natural logarithm of the number of employed workers per square kilometer in the LAU-1 district in which the job seeker was registered with the PES. The measure is constructed from individual-level records in the ADMIN3 core files and refers to December 2011.

Female — Dummy variable equal to 1 if the worker is female, and 0 otherwise.

Age — Age of the worker at the time of registration with the PES. Age is represented by three categories: 25–34, 35–44, and 45–54 years.

Education — Highest educational attainment of the worker at the time of unemployment registration with the PES. Four categories are distinguished: (i) **Elementary** — elementary school or lower; (ii) **Lower secondary** — vocational training school programs providing qualifications for specific trades; (iii) **Upper secondary** — general secondary education and vocational secondary school programs leading to a secondary school leaving examination and including pre-vocational elements; and (iv) **Tertiary** — college or university education and postgraduate specialization programs.

Participate in training program — Dummy variable equal to 1 if the job seeker participated in an adult training program during the unemployment spell, and 0 otherwise.

Participate in public work — Dummy variable equal to 1 if the job seeker participated in a public employment program during the unemployment spell, and 0 otherwise.

Labor market experience — Total number of months spent in employment up to the date of unemployment registration. The measure includes both full-time and part-time employment spells but excludes periods of absence from employment, including parental leave and other intervening non-working spells.

Occupational tenure — Total number of months the worker had previously spent employed in the targeted occupation up to the date of unemployment registration.

Job tenure — Total number of months spent in an employment relationship with the last employer before becoming unemployed.

Log of average monthly wage in pre-UE job — Logarithm of the worker's average gross monthly wage at the employer preceding unemployment, calculated over the entire duration of the employment relationship. Wage data are right-censored at the 99th percentile, with values above this threshold replaced by the 99th-percentile value.

Share of local employment in targeted occupation — Share of employed workers in the job seeker's LAU-1 district who are employed in the occupation targeted by the job seeker. The measure is evaluated at the time of registration and captures the local prevalence of employment opportunities in the targeted occupation.

Share of local job seekers targeting the same occupation — Share of registered job

seekers in the worker's LAU-1 district who report the same targeted occupation. The measure is evaluated at the time of registration and captures the local concentration of job seekers competing for employment in the same occupation.

Share of agricultural employment — Share of employed workers in agriculture in the LAU-1 district in which the job seeker was registered. The measure is constructed by aggregating individual-level employment records from the ADMIN3 core file and refers to December 2011.

Share of manufacturing employment — Share of employed workers in manufacturing in the LAU-1 district in which the job seeker was registered. The measure is constructed by aggregating individual-level employment records from the ADMIN3 core file and refers to December 2011.

Share of public sector employment — Share of employed workers in the public sector in the LAU-1 district in which the job seeker was registered. The measure is constructed by aggregating individual-level employment records from the ADMIN3 core file and refers to December 2011.

Unemployment rate — Unemployment rate in the LAU-1 district in which the job seeker was registered. The measure is constructed from individual-level records in the PES and ADMIN3 core files and refers to December 2011.

Instruments

Log population density in 1880 — Natural logarithm of population per square kilometer in the district in 1880.

Railway connection in 1880 — Dummy variable equal to 1 if the district had a railway connection in 1880, and 0 otherwise.

Additional historical controls

Share of literate population — Share of the population aged over 7 years who were literate in the district in 1880.

Share of Protestants — Share of the district population belonging to Protestant denominations in 1880.

Royal free city — Dummy variable equal to 1 if the district contains a settlement that held the status of a royal free city prior to the administrative reforms of 1876, and 0 otherwise.

Appendix C – Additional results and robustness checks

Throughout the analysis we considered workers who find employment within 24 months of registering as unemployed. Since occupational targets are observed at the

beginning of the unemployment spell, their relevance may decline as the unemployment spell progresses (see, e.g., Altmann et al. 2023). We therefore examine the sensitivity of our results to shorter reemployment windows of 6, 12, and 18 months. Table C1 reports the corresponding parameter estimates. Compared with the results reported in Tables 2 and 3, the estimates change only slightly across the alternative windows, indicating that our main results are not sensitive to the choice of the reemployment window.

We check the sensitivity of our results to three alternative sample definitions. First, we restrict the analysis to each worker's first observed unemployment spell. Since some individuals contribute multiple spells to the baseline sample, this restriction ensures that the estimates are not disproportionately influenced by workers who experience unemployment repeatedly. These workers tend to be less educated, have less labor market experience, and are disproportionately located in less densely populated areas. This raises the possibility that the estimated relationship between employment density and occupational search outcomes partly reflects the greater weight given to a relatively disadvantaged group of workers in thinner labor markets. Second, we restrict the sample to workers who experience only a single unemployment spell during the observation period. This more restrictive specification excludes workers with repeated unemployment altogether. Finally, we reestimate the models including workers who return to their previous employer. These workers are excluded from the baseline sample because such spells may reflect a temporary interruption of an existing employment relationship rather than a period of active search for a new employer.

Table C2 reports the results. Relative to the corresponding specifications estimated on the final sample, all three alternative samples yield somewhat smaller point estimates for log employment density. Nevertheless, the estimated coefficients remain statistically significant at the 1 percent level in every specification. The largest attenuation occurs when the sample is restricted to workers who experience only a single unemployment spell. The smaller estimates for single-spell workers suggest that the relationship between employment density and occupational search outcomes may be stronger among workers experiencing repeated unemployment. One possible explanation is that these workers are more vulnerable to the limited employment opportunities available in thin labor markets. Alternatively, repeated unemployment may itself partly result from poorer previous job matches. Restricting the sample to single-spell workers may therefore select a more stable group of workers for whom local employment density matters less. Overall, the qualitative pattern of the results is unchanged across the alternative sample definitions.

Table B1 Sample construction

Sample restriction	Retained spells	Percent dropped	Retained workers	Percent dropped
Registered as unemployed between 2012 and 2015 and aged 25–54 at registration	513,946		397,584	
Reemployed within 24 months	450,459	12.4	345,741	13.0
Excluding recalls to the previous employer	429,448	4.7	344,703	0.3

Notes: Retained spells and retained workers report the number of unemployment spells and unique individuals remaining after each successive sample restriction. Percent dropped indicates the percentage reduction relative to the sample retained in the preceding row.

Table C1 Alternative reemployment windows

Sample	Reemployed within 6 month	Reemployed within 12 month	Reemployed within 18 month
	(1)	(2)	(3)
Panel A: Reemployed in targeted occupation, (Full sample)			
Parameter estimates of log density	0.0071*** (0.0006)	0.0069*** (0.0005)	0.0071*** (0.0006)
Adj R-squared	0.142	0.135	0.131
Number of observations	370,563	377,861	411,175
Panel B: Skill similarity between targeted and post-UE occupations (Full sample)			
Parameter estimates of log density	0.0033*** (0.0004)	0.0032*** (0.0004)	0.0032*** (0.0003)
Adj R-squared	0.163	0.157	0.153
Number of observations	370,563	377,861	411,175
Panel C: Skill similarity between targeted and post-UE occupations (Reemployed in different occupation)			
Parameter estimates of log density	0.0034*** (0.0004)	0.0033*** (0.0004)	0.0033*** (0.0003)
Adj R-squared	0.153	0.094	0.097
Number of observations	207,490	265,602	291,745
Targeted occupation FE	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes
Employment history	Yes	Yes	Yes
Participation in training and public work	Yes	Yes	Yes
Local labor market characteristics	Yes	Yes	Yes

Notes: Each column within each panel presents the results of a separate regression estimated by OLS. All regressions include a constant and dummies for the year of registration. Individual characteristics include a female dummy, age-group and education dummies. Employment history includes labor market experience, tenure in the job preceding unemployment, and the log of average monthly wage in that job. Local labor market characteristics include the unemployment rate, the sectoral composition of local employment, the share of local employment in the targeted occupation and the share of job seekers with the same occupational target. Standard errors clustered at the district level are reported in parentheses.

*** $p < 0.01$

Table C2 Alternative samples

Sample	First UE spells only	Single spell workers	Including recalls
	(1)	(2)	(3)
Panel A: Reemployed in targeted occupation, (Full sample)			
Parameter estimates of log density	0.0064*** (0.0006)	0.0058*** (0.0006)	0.0061*** (0.0007)
Adj R-squared	0.129	0.129	0.134
Number of observations	304,902	216,205	450,457
Panel B: Skill similarity between targeted and post-UE occupations (Full sample)			
Parameter estimates of log density	0.0026*** (0.0004)	0.0022*** (0.0008)	0.0031*** (0.0003)
Adj R-squared	0.148	0.147	0.157
Number of observations	304,902	216,205	450,457
Panel C: Skill similarity between targeted and post-UE occupations (Reemployed in different occupation)			
Parameter estimates of log density	0.0028*** (0.0004)	0.0023*** (0.0004)	0.0034*** (0.0004)
Adj R-squared	0.092	0.095	0.092
Number of observations	218,510	155,606	313,048
Targeted occupation FE	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes
Employment history	Yes	Yes	Yes
Participation in training and public work	Yes		Yes
Local labor market characteristics	Yes	Yes	Yes

Notes: Each column within each panel presents the results of a separate regression estimated by OLS. All regressions include a constant and dummies for the year of registration. Individual characteristics include a female dummy, age-group and education dummies. Employment history includes labor market experience, tenure in the job preceding unemployment, and the log of average monthly wage in that job. Local labor market characteristics include the unemployment rate, the sectoral composition of local employment, the share of local employment in the targeted occupation and the share of job seekers with the same occupational target. Standard errors clustered at the district level are reported in parentheses.

*** $p < 0.01$