The Role of Occupational Mismatch in Unemployment and Post-Unemployment Outcomes*

Jonas Maibom[1,2] and Oskar Thorleifsson[1]

[1]Aarhus University
[2]IZA

PRELIMINARY DRAFT.

October 2024

Abstract

This paper studies the role of mismatch between unemployed job seekers and vacancies in shaping unemployment and post-unemployment outcomes. We build measures of how well job-seekers align with available vacancies and apply them to a sample of Danish UI recipients. We quantify the importance of mismatch to vacancies on several margins, including job finding, earnings, and occupational relocation. Workers who are mismatched with vacancies find a job slower and have lower earnings post-employment, even three years after unemployment entry. Furthermore, we exploit access to data on job applications submitted by unemployed workers to analyse the type of jobs targeted. We find an initial difference in the characteristics of jobs mismatched workers apply for. However, the change in application behaviour over the course of the unemployment spell is similar for mismatched workers and better matched workers. Lastly, we attempt to answer whether mismatched workers search differently in a way that alleviates adverse outcomes. By relying on counterfactual job-finding probabilities, we provide suggestive evidence that although mismatched workers direct a larger share of applications to unrelated jobs, this does not seem to translate into faster job finding.

Keywords: *Unemployment, Mismatch, Job Loss, Occupational Relocation, Job Search.*
JEL: *J24, J63, J64*

*This paper has benefited from numerous questions and comments from participants at several seminars, conferences and workshops. We thank Fane Groes and Michael Svarer for comments on early versions of the paper. We are grateful to the Danish Agency for Labor Market and Recruitment and the ECONAU project database (Department of Economics and Business Economics, Aarhus University) for making their data available. This paper was supported by the Independent Research Fund Denmark grant "Dynamic Effects of Education on Productivity and Labor Supply". Corresponding author: Jonas Maibom, maibom@econ.au.dk

1 Introduction

This paper studies the misalignment of unemployed job seekers and vacancies and its role in shaping unemployment and post-unemployment outcomes. Furthermore, it investigates whether mismatched workers search differently for jobs and if this matters for the outcomes. *Mismatch* is the misalignment of supply and demand for particular skills or human capital. The mismatch of unemployed workers with vacant positions contributes to the aggregate unemployment rate and its cyclical fluctuations (Şahin et al., 2014; Herz and van Rens, 2020).[1] However, when considering the costs of mismatch, this may only be a part of the story, and the effects of mismatch may materialise in more margins than slower job finding. On one extreme, one can imagine a world where workers quickly adjust to being mismatched with vacancies and quickly find a job that is not necessarily a good match for their skills. However, occupational switching can be costly for both workers and employers. At the other extreme, one could imagine that mismatch is realised to a greater extent in slower job finding, but to a more limited extent in earnings penalties and occupational relocation. This paper aims to quantify this empirically, and the sets out to answer the question: For which outcomes do the impacts of mismatch materialise and how much?

The second question this paper asks is whether there are differences in the way mismatched workers direct their job applications compared to other workers who match better with vacancies. That is, whether mismatched workers internalise their mismatch to vacancies and quickly expand on the area that they target jobs. Different theories have different predictions on this.[2] Additionally, behavioural biases such as overoptimism (e.g., Mueller et al., 2021) and information frictions (e.g., Belot et al., 2019) may be important determinants of job search and lead workers to search more narrowly than else would be optimal. Broader search may be an important channel that alleviates the adverse impacts of being mismatched to vacancies. We investigate this empirically by relying on counterfactual hiring probabilities for mismatched workers and decomposing the outcome gaps to what can be explained by differences in application behaviour.

We use several distinct data sources to make mismatch with vacancies measurable. Firstly, we build measures of occupational relatedness to measure the distance of unemployed workers to the job requirements of vacancies. We use these occupational relatedness

[1] Throughout, *mismatch* is used to refer to the misalignment of unemployed workers and vacancies in the same sense as Şahin et al. (2014), Shimer (2007), and others. In contrast to *ex post* mismatch, i.e. a misalignment of workers' skills and their jobs in the same sense as, e.g. Patterson et al. (2016) and Fredriksson et al. (2018).

[2] For example, Huckfeldt (2022) suggests that workers internalise slack sub-market conditions, and direct their search downwards to a less skill intensive market. Alvarez and Shimer (2011) suggest that for some workers, rather than relocating, it may be better to stay in the origin sub-market and wait for the slack conditions to improve.

measures combined with data on vacancies and unemployment by occupation and region to quantify the degree of mismatch to vacancies for each unemployed worker.[3] We apply these measures to a sample of unemployed workers, constructed from Danish administrative data. Using the mismatch measures, we quantify to what extent mismatch with vacancies matters for unemployment duration, mobility patterns, and earnings loss. In addition, we exploit access to data on job applications submitted by the unemployed workers to analyse the type of jobs targeted, as well as potential changes over the unemployment spell. Thereby, this paper provides new evidence on the mapping from initial (potential) mismatch to vacancies, to choices about job search and potential job finding as well as the characteristics of the eventual job. This evidence is crucial for quantifying the full consequences of mismatch at the individual level and also brings us closer to understanding some of the mechanisms through which the effect of mismatch materialises. Obviously, knowledge on the full consequences and potential mechanisms is important for both subsequent research and policy responses.

The paper begins by presenting measures to quantify how mismatched workers are with vacancies at the point of unemployment entry. The theory of mismatch is a theory of a segmented labour market and mismatch takes the form of dispersion of conditions in different sub-markets (Shimer, 2007; Şahin et al., 2014). We begin by defining a sub-market by the intersection of a worker's pre-unemployment occupation and region. The conditions in the sub-markets are measured by relying on vacancy data from *STAR* (the Danish Agency for Labor Market and Recruitment) that covers over 90% of posted vacancies in Denmark. Additionally, the count of unemployed insurance recipients by pre-unemployment occupation and geographical area are used to construct vacancy-unemployment ratios for each sub-market. The definition of a sub-market is then extended to include other occupations, to the extent that they are relevant by our measures of occupational relatedness.

We introduce several measures of occupational relatedness for this task. Furthermore, these measures are also used to distinguish between different types of occupational relocation.[4] Firstly, we rely on data from the Occupational Information Network (O*NET) database, developed by the US Department of Labor. In particular, we measure how transferable human capital is between two occupations by relying on three O*NET descriptor domains: *Skills*, *knowledge* and *work activities*. All of which are important for determining the transferability of previously accumulated human capital to a post-unemployment occupation. Secondly, we construct an alternative measure of occupational relatedness based on which "direct" transitions, i.e. with at most a minimal stop in unemployment, are most likely to be observed in the data.

Using the measures of mismatch to vacancies, we turn to quantifying how important

[3]Throughout the paper the pre-unemployment job is used as a measure for workers' skills etc. A series of sample selection steps are taken to ensure this measure is highly relevant.

[4]I.e., to measure misalagniment to the job-requirements of the post-unemployment job in several ways.

mismatch is for several outcomes. In particular: job finding, earnings loss and relocation across occupations. Mismatch with vacancies is not randomly assigned. We address selection issues using two strategies. Firstly, by controlling for observables to the extent that that is possible. Secondly, by instrumenting the mismatch measure by the number of mass layoffs of others in the same sub-market. The exclusion restriction is that the mass layoffs of others does not affect ones outcome other than through sub-market tightness. Potentially, there may be issues that remain. However, by alternative strategies and a series of robustness checks, we show that there is signal in what we estimate. We find that mismatch to vacancies is important for both earnings loss and job finding. We find that a standard deviations increase in weighted sub-market tightness (≈ 0.30), the immediate earnings difference in the post-unemployment job to the pre unemployment is 1.5-2.1% higher, and the probability of finding a job in 3 months is 2.4 percentage points lower. In terms of magnitude, both estimates are approximately 10% of the sample average of the outcomes.

Next, we analyse whether there are differences in job search across unemployed individuals who are mismatched compared to better matched individuals. Differences in search strategies may be an important mechanism in amplifying or reducing the impact of being mismatched with vacancies. Using unique data on applied for jobs, we investigate differences in application strategies as a potential amplification or reduction mechanism for unemployment scars. We examine whether workers that are mismatched to vacancies search differently than other workers and whether they adjust their application behaviour differently over the course of the unemployment spell. We find that mismatched workers apply more broadly. In particular, on average, they target less related jobs and lower-wage jobs compared to workers better matched to vacancies. These differences are present from the first month of unemployment and throughout the unemployment spell. The change in the characteristics of applied-for jobs evolves similarly over the course of the unemployment spell. Thus, it does not appear that mismatched workers adopt broader strategies over the course of the unemployment spell compared to others. Rather, the results point to an initial adjustment by mismatch status only.

Given that mismatched workers apply for a more broad set of jobs and lower wage jobs compared to workers that match well with vacancies, an interesting question to ask is if targeting a broader set of jobs helps to alleviate adverse outcomes, namely slower job-finding and lower earnings in the post-unemployment job. If mismatched workers are targeting shorter queues where they have a decent chance of being hired, a broader search may result in faster job finding. However, if mismatched workers are targeting more jobs in which they have a poor chance of being hired, perhaps due to their previous skills and experience not being a good match, the consequences of a broader search may be different. The latter may be in line with some recent empirical evidence on broad search. For example, Altmann et al. (2024) document that workers who target unrelated occupations to a larger extent tend to find a job slower. Furthermore, van der Klaauw and Vethaak (2022) find that requiring unemployment insurance recipients to search more broadly reduces job finding.

We rely on counterfactual job finding probabilities, if mismatched workers had applied in a similar manner as a better matched comparison group, to decompose the gap in outcomes, between mismatched workers and a better matched comparison group, into a part that may be explained by application behaviour and residual part. We find that slower job finding is largely *explained* by differences in applications, which does not suggest that mismatched workers apply differently in a way that speeds up job-finding.

The paper contributes to the literature on mismatch in the labour market and its consequences. Firstly, access to good data on vacancies and new measures of occupational relatedness allow us to build new and better measures of mismatch to vacancies and post-unemployment job. Secondly, it contributes to the literature by examining the importance of mismatch in unemployment as a potential driver on many margins and assessing their relative importance. Third, we exploit a more credible variation to estimate the effects of mismatch to vacancies. This paper also contributes to the literature on the role of specificity of human capital for earnings losses following job loss by exploring the role of mismatch to vacancies (e.g., Huckfeldt, 2022; Macaluso, 2023). In particular, by shedding light on search strategies as a potential mechanism that amplifies or reduces unemployment scars. It is well known that job loss has long-lasting consequences for individual earnings, subsequent employment stability (Jacobson et al., 1993), and even health outcomes (see e.g., Schaller and Stevens, 2015; Sullivan and von Wachter, 2009). This paper studies one potential driver or amplifier of these consequences, namely the idea that workers who enter unemployed with skills that are not in high demand may have a harder time escaping unemployment. Thus, this paper is also connected to a recent literature documenting the consequences of job loss for earnings and seeks to understand the most important causes of the large losses (e.g., Gulyas and Krzysztof, 2020; Lachowska et al., 2020; Athey et al., 2023).

The focus on occupational mismatch is in line with recent work. For example, Huckfeldt (2022) documents that occupational switching has a higher incidence in recessions and that earnings losses after displacement fall primarily on those who find reemployment in a lower-wage occupation. Huckfeldt constructs a model in which hiring becomes more selective in recessions, so it becomes optimal for some workers to search for lower-skilled jobs. We build measures of downward transitions in terms of an occupational rank and measures quantifying how much workers switch occupations, and relate that distance to their mismatch to vacancies in unemployment. Measurement of mismatch is a challenge. Several measurement approaches exist in the literature. A seminal example is Gathmann and Schönberg (2010) that quantify occupational relatedness by distance in occupational task content and document its importance for wage growth. Guvenen et al. (2020) and Fredriksson et al. (2018) measure skills mismatch between workers and their jobs. Both rely on direct measurements of workers' abilities at a young age, but the former combine this with O*NET skills data for occupational requirements. Both find that a mismatch to a job comes with a long-lasting wage penalty, even though workers tend to later switch to a better matching job. This paper adds to this in two ways: by building distinct measures of mismatch, both to vacancies and post-unemployment job, and examining mismatch in unemployment as a driver of occupational mobility, and thus potential mismatch to post-unemployment job.

Two other recent papers construct measures of the remoteness of a worker's human capital and investigate its contribution to earnings losses of displaced workers. Macaluso (2023) constructs a measure of *local skill remoteness* that measures the dissimilarity between the skill profile of a laid-off worker's previous job and other jobs (not vacant jobs) in the local labour market. Martinez et al. (2022) construct a measure of *knowledge specialization* which measures if it is important to have knowledge in few areas.[5] Both find that more remote workers suffer larger earnings losses following displacement. Neither studies the role of unemployment length. Both measure remoteness of occupation in general, but do not measure remoteness by accounting for conditions in the relevant sub-market in unemployment. Conversely, our measurements of remoteness contain three ingredients: measures of job-finding conditions in the occupational-region sub-market, measures of occupational remoteness, and measures of job finding conditions in other sub-market to the extent that they are related. By combining these ingredients, we can build a more accurate and relevant measure of the extent to which workers are mismatched with vacancies. This paper further contributes by shedding light on the channel, from mismatch to vacancies to potential mismatch to post-job and earnings losses, by examining differences in application behaviour by mismatch status.

Other related papers on mismatch include Marinescu and Rathelot (2018) which analyse the distaste of unemployed workers for applying for distant jobs — both in terms of geography and occupational relatedness. They rely on data on application clicks from an employment website. Their focus is on geographical mismatch and how much it matters for aggregate unemployment. In that respect, it is closer to the literature on the consequences of mismatch in the aggregate (Şahin et al., 2014; Herz and van Rens, 2020; Darougheh, 2022; Barnichon and Figura, 2015; Baley et al., 2022; Patterson et al., 2016). In contrast, this paper focuses on the individual consequences of mismatch to vacancies, its role in shaping unemployment scars, and search strategies as a potential amplification or reduction mechanism for mismatched workers.

Our findings are also relevant for the literature on the determinants of job search, behavioural biases, and information frictions. Mueller and Spinnewijn (2023) highlight how

[5] This notion of knowledge specialization labels occupations where it is important to be knowledgeable in *certain combinations* of many areas as not specialized. On the contrary, occupations regularly regarded as not specialized like *Maids and Housekeeping Cleaners* score relatively high on their measure.

expectations about job-finding procespects determine job search decisions and thus post-unemployment outcome outcomes. Mueller et al. (2021) find that unemployed job seekers are overly optimistic about their job-finding prospects and search narrowly for a job that resembles their previous job. They argue that this is an important cause of long-term unemployment. We contribute by providing new direct evidence on the types of job that workers that match poorly to vacancies target, how this changes over time in unemployment, and by linking to hiring outcomes of the mismatched workers.

This work is related and relevant to the literature that looks at the effects of information treatments on unemployed workers (e.g., Belot et al., 2019; Altmann et al., 2022). Firstly, one insight from this literature is that indirect effects of information treatments and job search assistance matter (see e.g., Altmann et al., 2022; Gautier et al., 2018; Crépon et al., 2013). Thus, providing information to everyone may not improve anything. We find evidence that mismatched workers may be a particularly vulnerable group. They suffer worse outcomes and direct applications in a way that does not seem to speed up job finding. Our measure of mismatch to vacancies may offer a way to detect workers who are vulnerable to unemployment scars. Thus, it may be useful for effective targeting for job search assistance.[6]

Secondly, another insight from this literature is that for a small treatment intensity, information is often particularly valuable for individuals in slack labour market (e.g., Altmann et al., 2022). This is a particular cut of the data and may represent other things; we try to use a more credible variation in mismatch with vacancies. This study also directs focus on the mismatched control group. We argue that it is important to understand how the mismatched control group is searching to understand the nature of the treatment effect providing information uncovers. Whether the control group has already broadened their search (potentially, ineffectively) and is the information treatment broadening on top of this – or is the control group searching as if they are not in a slack market – has implications for the nature of the treatment effects estimated.

Organization: The next section presents the data sources and the construction of the sample. The third section presents the measurements of occupational relatedness and mismatch with vacancies. The fourth section describes the empirical strategy. The fifth section quantifies the role of mismatch with vacancies for unemployment, earnings and occupational relocation. The sixth section investigates differences in application behaviour by mismatch. The seventh section presents the decomposition. The eighth section concludes.

[6] Of course, whether workers who are most mismatched to vacancies (and thus perhaps have high predicted losses) will benefit the most from an intervention requires an evaluation of the intervention in question. These workers may also suffer these losses despite the intervention, while others, less mismatched, may benefit from the same intervention.

2 Sample

To study the role of mismatch to vacancies, we construct a sample using Danish register data. We construct a data set of unemployment spells from administrative data on unemployment insurance (UI) payments from *DREAM*, an event-history data-base created by the Danish Ministry of Employment. We select workers who enter unemployment (begin receiving UI payments) from January 2011 to December 2020.

Unemployment insurance in Denmark is a system of voluntary membership of UI funds. Eligibility requires being a contributing member of one of the funds for a certain period of time before entering unemployment. The replacement rate is 90% with a cap of 19,728 DKK (in 2023). Fully eligible workers can receive benefits for up to two years. Employment for one year resets the eligibility period. To remain eligible, recipients must conduct active job search and regularly show evidence that they meet this requirement.

The data on UI spells is merged with information on job spells. The sample of job-spells is constructed from Danish administrative data on jobs. In particular, BFL, the Employment Statistics for Employees, which contains monthly information on hours and earnings for the universe of employed workers. This is merged with information on individuals, e.g. on gender, obtained from the population register, *BEF*. This data is used to create a sample of job spells, i.e., consecutive months an individual is employed in the same establishment.

Unemployment spells are merged to a pre-unemployment job by the unemployment start month being the same as the job-spell end month, or up to two months before or later. For the vast majority, this is in practice the same month. We consider the post-unemployment spell to be the first job spell subsequent to unemployment that lasts at least 3 months. Various information is collected on the job-spells. Importantly, this includes monthly earnings and reported hours. As well as the DISCO occupation code at the beginning of the post-unemployment job-spell and the end of the pre-unemployment job-spell.[7]

Both the measurements of the relatedness of the pre- and post-unemployment occupation of workers and the assignment of a unemployed worker to a sub-market, relies on the pre-unemployment occupation being a good measure of workers' skills etc. Therefore, we aim to exclude those from the sample where the pre-unemployment occupation is less likely to provide a solid foundation for building these measurements. To this purpose, the sample is restricted to workers whose pre-unemployment job spell lasted either at least 12 months; or 6 months complemented by 12 months cumulative *recent* occupational experience in the pre-unemployment occupation.[8] Workers currently in education are excluded from the sample.

[7]The DISCO classification system is the Danish version of the international occupation classification system ISCO. It is briefly described in Appendix D.

[8]For everyone, we require at least 6 months of occupational experience in the pre-unemployment occupation. Here, *recent* means from 2010 due to a break in the DISCO classification system in that year.

Those are also excluded who have completed their highest level of education in the past three years, at the time of unemployment entry.[9] To this end, the DISCO code 99 "students and interns" is also dropped. Furthermore, to restrict to approximately full-time workers, we require the average earnings of the job-spell to be above 13.000 kr.[10]

Workers older than 60 years are dropped and a minimum age of 18 is required.[11] The analysis is limited to those who are in unemployment for a period of at least 4 weeks. The workers that return to the same establishment post-unemployment, are excluded as they are not of interest in the analysis of mismatch unemployment. Some important information is required to be non-missing, including the DISCO code in pre-unemployment occupation and data on education. Finally, due to limited information on sub-market conditions, we drop those in the (pre-unemployment) DISCO main-group occupations 6 *work in agriculture, forestry and fishing* and 0 *military work*. This leaves us with a sample of 237 thousand workers.

To relate the results to the literature on the consequences of job loss - and to alleviate concerns about endogenous entry into unemployment - we additionally consider a sub-sample of displaced workers coming from mass layoffs. A worker is defined as displaced if (1) the worker separates from an establishment, (2) in the year of separation, the average number of employees at the firm shrinks by at least 30%, (3) the worker has been employed at the establishment for at least 12 months, and (4) the post-unemployment job-spell is not with the same firm. Note that conditions (1) and (4) are already fulfilled by the entire sample. For the calculation in (2), we require a minimum firm size of 20 average workers over the year. Leaving us with a displaced sub-sample of 22 thousand workers. Descriptive statistics on the sample and displaced sub-sample are presented in Table A1 in Appendix A.

We define a post-unemployment job spell as the first job spell subsequent to an unemployment spell that lasts at least 3 months with monthly earnings at least 4.000 kr. Some workers do not exit unemployment directly to another job. In the analysis, mismatch with vacancies is linked to the *immediate* change in earnings. Mismatch with vacancies is measured by assigning workers to a sub-market depending on the skills used in the pre-unemployment job. As time from the pre-unemployment job grows, especially for those who exit the labour market following unemployment, the pre-unemployment job perhaps becomes less relevant. For this reason, the part of the analysis that compares pre- and post-unemployment job to workers who find a job within 18 months of starting unemployment. We also require a

[9]We acquire data on the education of workers from the register UDDA. We also exclude those who have in the 3 years prior to job loss received educational grants (SU grants), drawing information from the DREAM register.

[10]All monetary amounts presented, including monthly earnings, have been adjusted for CPI changes since January 2008. Unless otherwise stated, the monetary amounts presented in the paper are in 2008 units.

[11]Note that the educational requirements cut out many younger workers.

gap of less than 6 months between end of UE period and start of the post-unemployment spell. This includes the analysis on distance between the pre- and post-unemployment job spells, immediate earnings difference, occupational switching, etc. Additionally, information on the post-unemployment firm, occupation, etc., is required to be non-missing. This is a sub-sample of nearly 164 thousand workers (about 15 thousand displaced workers).

Table A2 provides descriptive statistics for this sub-sample on post-unemployment earnings, hours and job spell duration. It also provides a comparison of the earnings, hours and wages in the last and first months of the pre- and post-unemployment job respectively. We define *immediate earnings difference* as the log of average monthly earnings in the first five months in the post-unemployment job, excluding the first month minus the log of average monthly earnings in the last five months in the pre-unemployment job, excluding the last month.[12] Thus, a negative number indicates an earnings loss. Here, earnings is a narrow salary amount per month, which includes salary income without employee benefits. For those with a post-unemployment job spell shorter than 5 months, the available months are used to measure the average earnings post-unemployment (still, excluding the first and the last month). Immediate wage (earnings per hour) and hour difference are defined in a similar manner as the immediate earnings difference.[13] For the analysis, the immediate differences are winsorized at the 1% lower limit and 99% upper limit.

3 Measures of Mismatch

To measure the misalignment of unemployed job-seekers and vacancies, we first build measures of occupational relatedness that are used to define a relevant sub-market of the labour market, together with geographical region. Misalignment of job seekers and vacancies is then measured by job-finding conditions in these sub-markets, measured by the vacancy-unemployment ratio. This section presents the measures.

3.1 Measures of Occupational Relatedness

3.1.1 O*NET Measures

To construct a measure of occupational relatedness, we use data from the Occupational Information Network (O*NET) database developed by the US Department of Labour. The database currently contains descriptors on more than thousand occupations. The goal is to

[12] The first and last months are excluded, as they may not represent a normal months earnings, e.g. if separation (job start) does not occur at the end (beginning) of the month. Moreover, to avoid severance payments, potential settlements, etc.

[13] Note that by this definition, for an individual, immediate earnings difference is the sum of immediate wage and hours difference.

measure how transferable the human capital of a worker that has been working in occupation *j* is to a destination occupation *k*. For the analysis, three of the O*NET descriptor domains are selected: *Skills*, *knowledge* and *work activities*. Respectively, containing 35, 33, and 37 standardised elements (i.e., all occupations are assessed on the same elements).

These are domains similar to those selected to construct the *O*NET career changers matrix*, developed to identify occupations that workers can directly transfer from their previous job and experience (see, O*NET, 2012). In the literature, there are examples of authors that rely on one of these domains to characterise workers' remoteness. For example, Macaluso (2023) considers *skills*, Martinez et al. (2022) consider *knowledge* and Gathmann and Schönberg (2010) consider *tasks* (but using a different data source). Indeed, all are likely to be highly relevant for a worker's decision of a destination occupation, that seeks to limit loss of use for accumulated human capital.

The assessment of *skills* is performed by occupational analysts, but *knowledge* and *work activities* are performed by occupational incumbents. Each element is evaluated with respect to level (**lv**) and importance (**im**).[14] So, an occupation *j* is described by 6 vectors, each consisting of 33-37 standardised elements:

$$O^j = \{\mathbf{s^j_{lv}}, \mathbf{s^j_{im}}, \mathbf{k^j_{lv}}, \mathbf{k^j_{im}}, \mathbf{wa^j_{lv}}, \mathbf{wa^j_{im}}\}$$

The procedure to map the O*NET data to the Danish DISCO occupations is described in Appendix D

O*NET Distance Meausre

The distance between two occupations *j* and *k* is quantified by calculating the Euclidean distance in terms of O^j and O^k. The distance from an origin occupation to itself is 0. For each occupation *j* We define the ten occupations with the least distance as *related* by the O*NET measure. Table A3 reports the ten most and the ten least related occupations for the DISCO occupation 2621 *Work in Economics*, 3354 *Issuance of Passports* and 5212 *Street Food Sales*. According to the DISCO main classification groups, *Work in Economics* requires skills at the highest level of knowledge, Issuance of Passports requires knowledge at the intermediate level, and the last example is work in service and sales. They should give examples for occupations at different levels of specialisation. Figure A1 shows the distribution of distance from these three origin occupations to other occupations for these three occupations. The figure shows differences between the occupations in that work in economics is more distant to other occupations, including its 10 most related occupations, capturing

[14] E.g. the level of maths skills that are needed and the importance of math skills for work in a certain occupation. The importance of the elements is assessed on a scale from 1 to 5 and the level on a scale of 0 to 7. We begin by standardizing the data so each element has a mean of 0 and standard deviation of 1.

increased specialisation.

O*NET Clusters

An alternative way of defining two occupations as related or not is to apply clustering methods to group related occupations in terms of the O*NET attributes. To offer an alternative to the previously presented measure of relatedness, we choose a correlation-based distance measure. That is, the dissimilarity of occupations *i* and *j* is measured by $1 - \text{corr}(O^j, O^k)$. A hierarchical clustering algorithm is applied such that each occupation starts as its own cluster and the pair that is most similar (correlated) is merged. The algorithm proceeds to compute the new pairwise intracluster dissimilarities. We use complete linkage clustering meaning that the maximal inter-cluster dissimilarity is considered. The algorithm proceeds until all occupations are in one cluster. To determine the number of clusters, we choose a threshold of 0.7, such that the minimal correlation between two occupations in the same cluster is always greater than 0.7. This results in 188 clusters. The choice of this threshold is stricter than the alternative decision to label the top ten least distant occupations as related. That can be seen from the fact that the average number of occupations in a cluster is 2.2. 94 four-digit disco occupations are its own cluster. The largest cluster contains 12 occupations. The distribution of the size of the clusters is depicted in Figure A2.

To link to earlier examples, here Work in Economics (2631) is clustered with work with mathematical, actuarial, and statistical methods and theories (2120) and work with statistics and mathematics (3314), the two most related occupations according to our Euclidean distance measure. Issuance of passports is grouped with customs and border guards works (3351), provision of public services (3353) and legal work at the intermediate level (3411).

O*NET Principal Components

The O*NET distance measure is useful to rank potential destination occupations in terms of relatedness. However, it does not allow for the distinction between upward or downward movements in the skills, knowledge, and task spaces. One strategy would be to look at the differences in the importance and level of all the skills, knowledge, and task elements considered. The problem is that, all together, they count 210 elements. In an attempt to achieve this distinction, we reduce the O*NET data to three principal components, keeping 63% of the variation in the data. The first principal component is a linear combination of the O*NET elements that preserves the most variation of the 4 digit disco occupations in terms of the O*NET elements. The second component is a linear combination of the O*NET elements that is uncorrelated with (orthogonal to) the first principal component and has the largest variance. Similarly, the third component is the linear combination that is orthogonal to the first two and has the largest variation. In our case, the gains of adding the fourth component are limited with respect to the increase in preserved variation.

The first component, which we label as *"active learning, etc."*, is most positively correlated (loaded) with active learning, critical thinking, and speaking; it is most negatively correlated (loaded) with handling and moving objects, performing general physical activities and repairing. The second component, which we label as *"service skills"*, is most positively correlated (loaded) with working with the public, service orientation, customer knowledge, and personal service. It is negatively correlated (loaded) with mechanical knowledge, quality control analysis, and knowledge of engineering. The third component, which we label as *"math and programming"*, is most positively (loaded) correlated with programming skills, computer knowledge, mathematics skills and knowledge. It is negatively (loaded) correlated with assisting and caring for others, knowledge of therapy, and knowledge of public safety.

Figure A3 shows four-digit DISCO occupations in terms of the first two principal components coloured by the main occupation group. The first component ("active learning, etc.") preserves some of the hierarchical order of the DISCO main group classification.[15] More variation is apparent in this respect with the second component. Consider, for example, two occupations, 2142 *engineering work related to buildings* and 2310 *teaching and research at universities*. Both score similarly high on the first component. The latter also scores relatively high on the second component, while the former scores low.

Table A4 reports estimation results of a regression of immediate earnings difference on an indicator of switching downwards, defined by having a higher score of the principal components in the pre-UE job compared to the post-UE job. The top ten related occupations, measured by the O*NET measure are not counted as downwards move. We see that moving down measured by the first and third are associated with larger earnings losses on average. If we rank the clusters of related occupations by averages wages in the sample period (using wage data for the universe of workers in the occupation in this period; not only the sample) and define a downwards move by moving downwards in this rank, we see that is associated with a substantially larger earnings loss (half of the sample average). In comparison, moving down a standard deviation on the O*NET measure is also correlated with lower earnings in the post-unemployment job. However, the estimate is in comparison small, highlighting the importance of distinguishing between upwards and downwards move in the skill space. Moving downwards on principal component two is associated with a small earnings gain. Perhaps its negative loadings are more market valuable skills than its positive loadings. In this light, our measures of downwards transition for subsequent analysis, will be based on moving down on the first principal component and switching downwards in terms of the in the O*NET cluster wage rank.

[15] I.e., 1 is management, 2. Work that Requires Knowledge at the Highest Level, 3. Work that Requires Knowledge at the Intermediate Level, and so on.

3.1.2 Observed Transitions

Another way to quantify the distance of a transition from *j* to *k* is to ask if this is a transition that is frequently observed in the data. To operationalise this, we construct a sample of workers from 2011 onwards.[16] We select a sample of approximately full-time workers (full-time equivalence > 0.9) and restrict to prime-age workers (30-55 years old). The transitions between all DISCO occupations, on all five levels of dis-aggregation, are counted. Transitions both within and between job spells are counted. For the latter, we restrict to those transiting to a new job within 30 days. Based on this, a transition matrix is constructed where an element (j, k) is the probability of observing a transition from an origin occupation *j* to a destination occupation *k*. The diagonal of the matrix represents the probability of staying $P(j, j)$. Note that origin occupation transitions (i.e. occupational staying) are counted not only between spells, but also to the extent possible within spells. That is because the count includes transitions between 6 digit DISCO occupations but within a four- or two-digit DISCO occupation as an own occupation transition at the appropriate level.

To measure the relatedness of occupations, a transition matrix conditional on switching occupations is constructed. We define a related occupation as the ten most likely transitions conditional on switching.[17] One way to examine the transitions in our sample of unemployed workers is to construct a similar transition matrix using our sample of unemployed workers and look at the difference from the observed transitions in the labour market. Figure A4 shows the difference of the conditional transition matrix at the 1 digit DISCO level using our sample from the similarly defined matrix of observed direct transitions in the labour market. For example, the probability of observing a transition from *work that requires knowledge at the highest level* to *management* is 21 percentage points lower in our sample of unemployed workers compared to "direct" occupational transitions in the labour market. The figure shows that workers in the unemployed sample are less likely to transit to a destination occupation above the diagonal, or in particular to the first three main groups, and are more likely to transit to a destination below the diagonal. Suggesting that in our sample of workers that suffer unemployment, we observe more downward transitions, in terms of the hierarchical order structure of the DISCO system.

3.2 Mismatch to Vacancies

We now turn to quantifying unemployed job seekers' degree of mismatch to vacancies at the point of unemployment entry. The theory of mismatch is a theory of a segmented labour market and mismatch takes the form of dispersion in job-finding conditions in sub-markets

[16] Using the same data sources as described in section 2.

[17] Top three for the main group classification level.

(Shimer, 2007; Şahin et al., 2014). We quantify mismatch to vacancies by measuring the conditions in the relevant sub-market in the month of unemployment entry. We define a sub-market by the intersection of a worker's pre-unemployment DISCO occupation and geographical area. Then we expand the sub-markets, to also include other occupations, to the extent that they are related.

The primary specification is the intersection of a 2 digit DISCO code and 4 regions; Capital region & Zealand, Northern Jutland, Mid-Jutland and Southern Denmark. Then sub-markets are expanded using the transition-based measure of occupational relatedness. We report additional results based on alternative versions, using the O*NET data to define the relatedness of occupations. Our primary version uses the three-month average, centred in the unemployment start month, to count vacancies and unemployment. We assess the robustness of the results with respect to using the unemployment start month count only, quarterly counts or 5 month averages.

The count of vacancies in the sub-markets in each month is obtained using data on vacancies from *STAR* which contains all job postings on *Jobnet*, the public job centres' website for job seekers and employers. The data also includes job postings elsewhere on the Internet, including web-scraped postings. The vacancy data has a very high coverage of job postings in Denmark, covering more than 90% of (online) vacancy postings. The data contain various information on the job postings. Crucially, this includes the period in which the job posting is active, the establishment's municipality code, an occupation code, and the number of available positions.

The count of unemployed workers is obtained by the pre-unemployment occupation of workers that receive unemployment insurance in each month. Here, we consider only unemployed workers directly entering unemployment from employment with a gap of no more than 2 months. For other workers, it is less natural to directly define their sub-market by pre-unemployment occupation. Using the count of unemployed workers by occupation and region combined with our vacancy data, the vacancy unemployment ratio for occupation o in region r in month t is constructed as $\theta_{o,t,r} = \frac{v_{o,t,r}}{u_{o,t,r}}$[18]

The relevant vacancies and competition an unemployed worker faces are not only those within her pre-unemployment occupation, but also in related occupations. Conditions in other occupation-submarkets matter to the extent that the occupations are related. To capture this, we make use of the relatedness measure presented in the previous subsection. In particular, the observed direct transition matrix. To measure how tight the market is for

[18]We require at least 10 vacancies and 10 unemployed workers in a sub-market to construct the vacancy unemployment ratio in the market. This condition is rarely binding. The tightness measure is winorized at the lower limit 1% and the upper limit 99% with respect to the tightness distribution of submarkets, before applying the measures to the sample, to avoid that the results are influenced by extreme values.

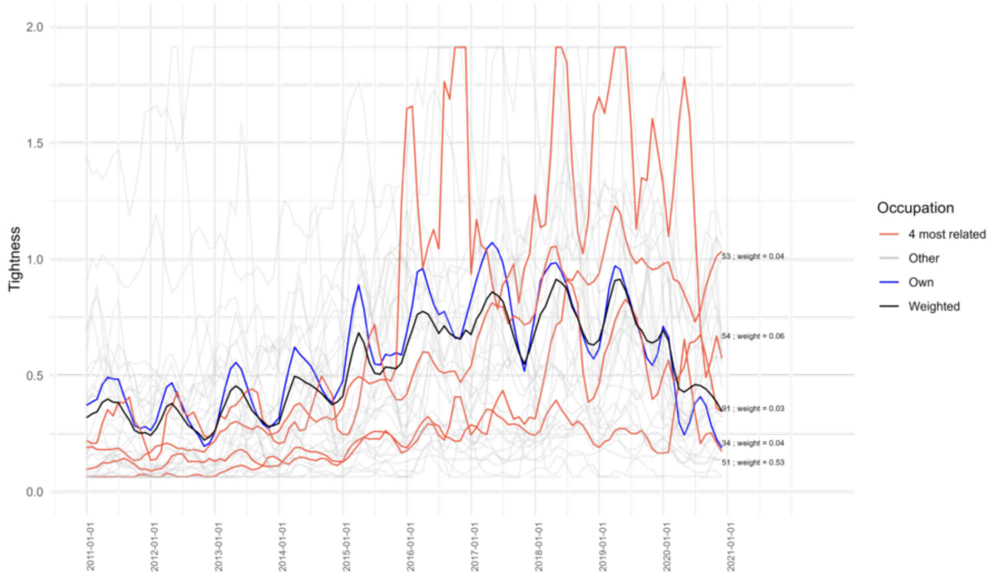


Figure 1: Weighted sub-market tightness for DISCO occupation 51 Work in service in Zealand
The figure compares weighted sub-market tightness (black line) to origin occupation tightness (blue line). It highlights the contribution of the most related 2 digit occupations (red line). They contribute according to the weights specified in the figure. The grey shaded lines show other occupations that contribute with a lower weight.

an unemployed worker of a pre-occupation *i* we calculate the weighted tightness:

$$\tilde{\theta}_{i,t,r} = \sum_{k} P(i,k)\theta_{k,t,r} \tag{1}$$

where the tightness in the origin occupation sub-market $\theta_{i,t,r}$ is weighted by the staying probability $P(i,i)$. To illustrate, Figure 1 portrays the weighting scheme for one submarket as an example, service workers in Zealand, and compares to the weighted sub-market tightness to tightness considering only the origin occupation.

3.2.1 Alternative Versions

O*NET Clusters

Using the clusters of related 4-digit disco occupations, we count the number of vacancies and unemployed in each cluster and construct tightness measures. As the threshold for occupations to be clustered together is relatively higher, here we count each vacancy and unemployed in the cluster equally, i.e. not weighted by the degree of relatedness. Keep in mind that these clusters are still more disaggregated than the 2-digit DISCO groupings.

O*NET Weights

Unlike the transition-based relatedness measure, the O*NET measures offer no natural weighting scheme, i.e. one that does not rely on a seemingly ad hoc decision. If we consider the O*NET distance measure, the scale in which the distance is measured becomes important for a potential weighting scheme. One solution is to set a distance threshold beyond which other occupations have a weight of zero. A candidate for such a threshold may be the 0.33 quantile in the distance distribution of all pairs of four-digit disco occupations (≈ 17.4). In that way, we consider only somewhat related occupations to have a positive weight. Additionally, setting the threshold relative to the distribution of all pairs of four-digit occupations, rather than having a occupation-specific threshold, allows us to preserve that some occupations are more distant to others on average (e.g., more specialised).

The weights, ω, are constructed to decay proportional to the distance measure such that:

$$\omega_{i,k} = \begin{cases} 1 - \frac{\text{distance}_{o,k}}{\text{threshold}} & if \quad \frac{\text{distance}o,k}{\text{threshold}} \leq 1 \\ 0 & otherwise \end{cases}$$

Where again *o* is the origin occupation and *k* is the (potential) destination occupation. Here, the origin occupation itself receives a weight of 1. However, the sum of the weights may sum up to a number that is different from 1, and the sum becomes larger if the occupation is closely related to many other occupations. For each occupation *o* in a particular region at a given time, we use $\omega_{i,k}$ to construct a weighted count of vacancies and a weighted count of unemployed resulting in a measure of tightness in the sub-market.

Binary Mismatch Definition

For part of the analysis, in particular, the analysis of application behaviour by mismatch, we rely on a binary definition of mismatch. Mismatch at a given point in time takes the form of dispersion in conditions across sub-markets. A mismatched worker is someone in a sub-market where job-finding conditions are (relatively) bad while conditions are (relatively) good in some other sub-markets. For some of our analysis, we say that a worker is in *mismatch unemployment* if she belongs to the bottom quartile in the rank of sub-markets by weighted tightness at the point of unemployment entry.

4 Empirical Set Up

The treatment of interest is mismatch to vacancies, measured by weighted sub-market tightness, at the month of unemployment entry. The primary measure for the empirical analysis is based on the transition-based measure of occupational relatedness and uses the three month average of vacancies and unemployment, centred in the unemployment start month. Results using alternative versions of the measures are presented in Appendix A

In essence, we will adopt the following econometric specification:

$$y_{i,o,r} = \alpha + \beta\tilde{\theta}_{i,o,r} + \gamma x_{i,o,r} + \epsilon_{i,o,r} \tag{2}$$

Where $\tilde{\theta}_{i,o,r}$ is the weighted sub-market tightness in the unemployment start month of individual *i* in occupation *o* and region *r*. $x_{i,o,r}$ are set of controls including individual characteristics, occupation and region that are further discussed below. Often the outcome, $y_{i,o,r}$, is of the form post minus pre, e.g. earnings difference, so individual time invariant factors, that may correlate with sub-market tightness and the outcome, are accounted for.

There may be present selection issues that one may worry about. Firstly, weighted sub-market tightness is not randomly assigned. For example, mismatch may tend to be higher in rural areas, and earnings loss as well. But it may be the case that search frictions are also greater in these markets. And thus earnings loss is higher because of larger search frictions rather than tightness. Or, for example, that in some rural areas there are stronger locational preferences such that individuals value less commuting time more compared to earnings, leading to larger earnings loss.

Seccondly, one may worry about systematic differences in recruitment across occupations. That is, in different occupations, a given level of weighted sub-market tightness may have a different meaning because there are many (few) jobs to get that are not posted online or more (less) competition from employed workers (rather than unemployed workers). In that case, we might, for example, worry that occupations with more informal hiring may also tend to have binding minimum wages, so earnings loss is lower.

4.1 Observables

To the extent that we can, we address this by controlling for observables $x_{i,o,r}$. This includes pre-unemployment occupation fixed effects, to account for the concern that different levels of tightness may mean something different in different occupations. This also includes commuting zone fixed effects to address regional differences in other factors as a potential confounder.

$x_{i,o,r}$ also includes individual characteristics that could potentially correlate with mismatch and the outcome such as gender, level of education, gender, and age. Probably, this is even more important for the outcome variables that are not in a difference form (i.e., post minus pre). However, in principal, one could imagine that, for example, older workers belonging to more slack markets and also having larger earnings penalties because they are older rather than being mismatched.

Note that by adding pre-occupation fixed effects, we absorb things that we want to keep fixed. In the sense that by using within occupation variation in sub-market tightness for identification, we account for the fact that a given level of V or U may mean something different in different occupation. Then we use variation over time and region. However, pre-unemployment occupation fixed effects explain over half of the variation in the mismatch measure. To the extent that mismatch is time-invariant for some occupations ("dead end" occupations), they no longer provide identifying variation. Due to the concerns described above, our preferred specification still includes pre-unemployment occupation fixed effects.

4.2 Instrument: Mass Layoffs of Others

Another strategy we use to address the selection concerns is to instrument weighted sub-market tightness by the mass layoffs of others in the same sub-market (defined by pre-unemployment occupation and region) at the month of unemployment entry. The number of mass layoffs is divided by the population of the region, so the instrument for worker *i* takes the form: $\frac{\#\text{ mass layoffs}}{\text{population}}_{i,r,o,j\neq i}$

As when defining our *displacement* sub-sample, we use a data-driven definition of a mass layoff. That is, if, the establishment shrinks by at least 30% between years, the individual separates from the firm and starts receiving unemployment insurance benefits, we define the individual as having been subject to a mass layoff. However, if the count of mass layoffs is zero in too many sub-markets, that may undermine the extent that the instrument is relevant. Thus, we reduce the requirement of the firm size that 30% reduction is calculated relative to before. Before, we required a firm size of 20 workers on average over the year. We now make the restriction that the reduction in employment at the establishment is at least 5 workers between years.[19] This restriction becomes binding for an establishment size smaller than 16.7 average workers over the year. For example, an establishment of 10 workers would have to reduce in size by half, and an establishment with 5 workers would have to elude existence.

We leave the individuals in our sample that are subject to mass layoffs out when constructing their own instrument due to concern about mechanical correlation. Our primary version of the instrument uses the same weighting scheme when constructing the instrument for each sub-market as in equation (1). We assess the robustness of the results to only using the origin occupation mass layoff count and using only mass layoffs in related occupations.

There may be systematic differences between industries or occupations in their use of mass layoffs. A concern may, for example, be that occupations that use mass layoffs more have a more binding minimum wage, and thus lower earnings loss. To address these concerns, we subtract the occupation means when constructing the instrument:

$$\widehat{\frac{\#\text{mass layoffs}}{\text{population}}}_{i,r,o,j\neq i} = \frac{\#\text{mass layoffs}}{\text{population}}_{i,r,o,j\neq i} - \overline{\frac{\#\text{mass layoffs}}{\text{population}}}_{o,j\neq i}$$

[19] If more than 70% of the establishment leavers transit to the same establishment, we drop them from the count.

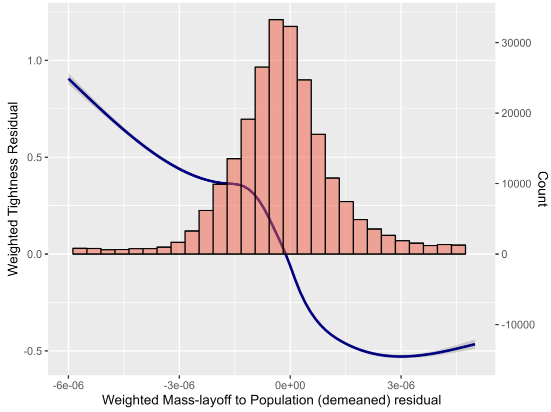


Figure 2: Residualised instrument an residualised weighted tightness
The horizontal axis shows weighted mass layoffs to population, where occupation means have been subtracted, on the horizontal axis and weighted sub-market tightness on the vertical axis (left axis). Both are residulised according to column 3 of Table 1. The line shows a smooth conditional mean of weighted tightness residuals conditional on weighted mass layoffs to population residuals. The histogram shows the number of observations in the bins (right axis).

Similarly to the displacement sample, workers coming from shrinking firms that enter unemployment insurance are considered subject to mass layoffs. The requirement to enter UI is an attempt to ensure that we truly count workers who suffer mass layoffs. However, whether a worker who is a subject to a mass layoff actually enters unemployment - in contrast to finding another job while on notice - is likely a function of sub-market conditions. This may potentially cause bias in the first stage. We still prefer this condition on the workers entering UI to ensure the count does not include other things, for example, establishments of production moving to two new establishments. That else might be incorrectly counted as mass layoffs. However, to address this concern, in robustness checks, we also present results using a version of the instrument where we do not require UI entry, which give similar results.

Intuitively, more mass layoffs in a sub-market predict lower tightness. Table 1 reports a estimation results of a first-stage regression in several specifications that are used in the next section. Showing that we have a relevant first stage. Figure 2 shows a residualised version of the instrument on the horizontal axis and a residulised weighted sub-market tightness on the vertical axis according to column 3 of Table 1. The figure shows the smoothed conditional mean of weighted tightness together with a histogram showing the number of observations in the bins. The figure shows that weighted tightness is monotonically decreasing in increased mass layoffs.[20]

The exclusion restriction is that the mass layoff of others does not affect individuals' outcomes other than through sub-market tightness. This may be a strong assumption. For example, worse economic conditions in the aggregate (locally) can lead to more mass layoffs

[20]Figure B1 shows a similar figure but with a log specification of weighted tightness, which we also use later.

Table 1: First stage: Mass layoffs and weighted sub-market tightness

Dependent Variable:	Weighted Sub-Market Tightness					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	1.742***			-3.264***		
	(0.0611)			(0.7515)		
Mass Layoffs to Population weighted (mean dev.)	-130,290.5***	-120,391.3***	-115,865.5***	-130,366.5***	-120,566.6***	-115,801.0***
	(17,058.8)	(15,791.4)	(15,372.2)	(16,997.3)	(15,322.2)	(14,787.7)
Log Pre Earnings				0.4906***	0.3191***	0.0434***
				(0.0732)	(0.0563)	(0.0102)
Fixed-effects						
Level of Education		Yes	Yes		Yes	Yes
Age (dummy for each value)		Yes	Yes		Yes	Yes
Female		Yes	Yes		Yes	Yes
Commuting Area		Yes	Yes		Yes	Yes
Pre-Unemployment Occupation (4 digit)			Yes			Yes
Fit statistics						
Observations	237,038	237,038	237,038	163,832	163,832	163,832
R^2	0.08811	0.22106	0.60476	0.11462	0.23978	0.62093
Within R^2		0.08739	0.14530		0.09737	0.14716
F-test (1st stage)	22,903.2	22,691.6	40,284.2	15,896.8	15,687.9	28,200.7
Wald (1st stage), p-value	2.22×10^{-14}	2.47×10^{-14}	4.81×10^{-14}	1.73×10^{-14}	3.6×10^{-15}	4.87×10^{-15}

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
The table reports a regression of weighted sub-market tightness on mass layoffs to populations (occupational means subtracted).
The specifications correspond to to Table 2 and Table 3

and higher earnings losses. That is fine if the channel is through less (local) demand for labour, and thus worse outcomes. But would be violated, for example, if there is a (local) productivity shock that leads to more mass layoffs, and earnings in the post-unemployment job are lower because productivity is lower. We still think of it as a very useful benchmark.

4.3 Unit of treatment

Weighted sub market tightness is standardised by the sample standard deviation (≈ 0.30). For the sample average tightness over time, it is approximately equivalent to going from 2013 to 2015. Going from 2011 to 2018 is a move of approximately 3 standard deviations. Between occupations, in the beginning of 2015, going from a health care worker (Disco code 22), a very well-matched occupation, to operator work at stationary plants and machines (Disco code 81), which faced a very slack market, is a move of 6.6 standard deviations. Alternatively, we will report estimation results using a log of weighted sub-market tightness. That specification may also be more compatible with the theory of the matching function. Appendix B reports results with this specification.

Table 2: Job finding in 3 months and weighted tightness.

Dependent Variable:	Finds a Job Within 3 Months (indicator)					
	OLS				2SLS	
	Entire Sample		Displaced		Entire Sample	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Weighted Sub-Market Tightness	0.0236***	0.0241***	0.0163***	0.0279***	0.0447***	0.0460***
	(0.0052)	(0.0028)	(0.0063)	(0.0061)	(0.0062)	(0.0054)
Fixed-effects						
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)		Yes		Yes		Yes
Fit statistics						
Observations	237,038	237,038	21,630	21,630	237,038	237,038
F-test (1st stage), Weighted Sub-Market Tightness					22,691.6	40,284.2
Wald (1st stage), p-value, Weighted Sub-Market Tightness					2.47×10^{-14}	4.81×10^{-14}
Mean dep. var.	0.2656	0.2656	0.2651	0.2651	0.2656	0.2656

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted sub-market tightness is standardised w.r.t. sample standard deviation (0.30).
The instrument is mass layoffs to population (occupation mean dev.).
The corresponding first stage is reported in Table 1.

5 Empirical Results

5.1 Job-finding

5.1.1 Job-finding in three months

Workers entering a tighter submarket have a higher probability of finding a job in 3 months. Table 2 reports regression estimation results of a regression of an indicator of finding a job within 3 months on weighted sub-market tightness. The first two columns present the results for the entire sample (the difference being the inclusion of pre-UE occupation fixed effects). A standard deviation (≈ 0.3) increase in weighted sub-market tightness is associated with 2.4 percentage points higher probability of finding a job in 3 months. The third and fourth columns report similar results using the displacement sub-sample. Including the pre-occupation fixed effects, which is our preferred specification, the estimate is similar. The two-stage least-squares estimates are reported in the fifth and sixth columns. The 2SLS estimates suggest that the effects may be even greater.

The mean 3-month job-finding probability in the sample is 0.27. A standard deviation's increase corresponds to an increase of 9% of the mean job-finding probability. The IV estimates suggest that this gives a lower bound. Table B2 shows the corresponding table in logs. The estimated semi-elasticity (column 2) is 0.024 and IV estimates again suggest that the effect of tightness on job-finding may be even higher.[21]

5.1.2 Job-finding in 6 to 18 months

Weighted sub-market tightness is measured at the unemployment start month. Therefore, one would expect the effects to be greatest when looking at job-finding within the first few months of the unemployment spell. Figure A5a reports regression estimation results of a regression of job finding in 6, 9, 12, 15 and 18 months on weighted tightness (using the same specification as columns 3 and 6 of Table 2).[22] Note that job finding in 6 months includes job finding within 3 months and job finding within 4-6 months. The OLS estimates are stable for job finding in 3 to 18 months. Suggesting that the initial tightness is still relevant as we move further away from the unemployment start month. Figure A5b shows the mean dependent variable. Compared to the mean of the dependent variable, the estimated effect diminishes when we consider a job finding in a longer period.

5.2 Immediate earnings difference

Next, we look at the effects of mismatch on immediate earnings difference. That is, we look at the pre minus post difference in earnings in the first and last months. A negative difference corresponds to an earnings loss. The empirical set-up here is similar to that in the previous subsection. We add control for earnings to capture that individuals with higher earnigns in the pre-unemployment job tend to have larger earnings penalties.

Table 3 reports estimation results of a regression of immediate earnings difference on weighted tightness. A standard deviation's increase in weighted sub-market tightness is associated with 1.5% higher earnings in the post-UE job (column 3). The estimates are slightly higher for the displacement sample or 2.0%. The IV estimates are similar to the latter; about 2.0%. Table B3 reports the results with log of weighted tightness. The estimated elasticity is 0.03. The elasticity estimates for the displacement sample and the 2sls estimates are similar, about 0.03.[23] To compare to existing estimate of the elasticity of wages with respect to tightness in Denmark, Hoeck (2022) estimates the elasticity of wages at the firm level with respect tightness as 0.01-0.02. Intuitively, one may expect that to be higher when considering new hires (and from unemployment only).

An increase in weighted tightness of about 1 standard deviation corresponds to about 10% of the average earnings loss following job loss in the sample. That is very similar in magnitude

[21] The mean of standardized weighted tighness is 1.68. 1.68*0.024 = 0.40. So, at the mean, it is a quantitatively similar estimate.

[22] Figure B2 shows a similar figure with results using log of weighted tightness

[23] At the mean the log estimates are slightly higher; 0.015*1.67 = 0.025

Dependent Variable:	Log Post Earnings - Log Pre Earnings								
	OLS						2SLS		
	Entire Sample			Displaced			Entire Sample		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Constant	3.334***			3.621***			3.343***		
	(0.1426)			(0.1826)			(0.1435)		
Weighted Sub-Market Tightness	0.0168***	0.0155***	0.0149***	0.0215***	0.0189***	0.0204***	0.0194***	0.0203***	0.0212***
	(0.0044)	(0.0031)	(0.0016)	(0.0048)	(0.0038)	(0.0034)	(0.0059)	(0.0051)	(0.0054)
Log Pre Earnings	-0.3451***	-0.4278***	-0.5211***	-0.3753***	-0.4585***	-0.5353***	-0.3464***	-0.4294***	-0.5214***
	(0.0137)	(0.0125)	(0.0121)	(0.0175)	(0.0163)	(0.0154)	(0.0140)	(0.0126)	(0.0122)
Fixed-effects									
Level of Education		Yes	Yes		Yes	Yes		Yes	Yes
Age (dummy for each value)		Yes	Yes		Yes	Yes		Yes	Yes
Female		Yes	Yes		Yes	Yes		Yes	Yes
Commuting Area		Yes	Yes		Yes	Yes		Yes	Yes
Pre-Unemployment Occupation (4 digit)			Yes			Yes			Yes
Fit statistics									
Observations	163,832	163,832	163,832	14,907	14,907	14,907	163,832	163,832	163,832
R^2	0.16657	0.21812	0.26449	0.20000	0.25966	0.32208	0.16649	0.21788	0.26427
Within R^2		0.20492	0.23121		0.24285	0.25834		0.20467	0.23097
F-test (1st stage), Weighted Sub-Market Tightness							15,896.8	15,687.9	28,200.7
Wald (1st stage), p-value, Weighted Sub-Market Tightness							1.73×10^{-14}	3.6×10^{-15}	4.87×10^{-15}
Mean dep. var.	-0.1546	-0.1546	-0.1546	-0.1819	-0.1819	-0.1819	-0.1546	-0.1546	-0.1546

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted sub-market tightness is standardised w.r.t. sample standard deviation (0.30).
The instrument is mass layoffs to population (occupation mean dev.).
The corresponding first stage is reported in Table 1.

Table 3: Immediate earnings difference and tightness

to what we found regarding job finding in 3 months relative to the same benchmark. If we instead benchmark the size of the effect to earnings we see that a standard deviations increase in weighted tightness corresponds to about 3% lower pre-unemployment earnings.[24] Previous research has highlighted that earnings loss following job loss tends to be very heterogeneous (Athey et al., 2023). In that light, the estimated effects are reasonably sizable.

It is not surprising that when sub-market tightness is higher, job finding is slower and earnings in the post-unemployment job are lower. However, it is important to quantify how much to understand how much mismatch unemployment matters. Additionally, ex ante, it is not clear which of these margins is more important. Compared to the sample means of, on the one hand, 3 month job finding and, on the other hand, the immediate earnings difference, the estimated effects represent a similar share, approximately 10%. By that benchmark, one could conclude that the effects on 3 month job finding and earnings are of similar magnitude.

5.3 Earnings in 0-3 years after UE entry

Next, we examine earnings beyond the first months of the post-UE job to answer whether the effects of tightness on earnings are temporary or if they are persistent in the longer run. For this analysis, we consider the entire sample but keep only the first spell of those that

[24] Looking at column 3: $\frac{0.015}{-0.521} \approx -3\%$

Dependent Variables:	Yearly earnings year of entering UE (kr.)	Yearly earnings 1st year after entering UE (kr.)	Yearly earnings 2nd year after entering UE (kr.)	Yearly earnings 3rd year after entering UE (kr.)
Model:	(1)	(2)	(3)	(4)
Variables				
Weighted Sub-Market Tightness	3,935.6***	9,801.5***	8,100.3***	5,865.2***
	(668.8)	(989.4)	(987.0)	(1,100.0)
Yearly earnings year before UE (kr.)	0.5965***	0.3528***	0.4057***	0.4058***
	(0.0184)	(0.0145)	(0.0146)	(0.0134)
Fixed-effects				
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes
Level of Education	Yes	Yes	Yes	Yes
female	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Fit statistics				
Observations	204,641	204,641	204,641	181,155
R^2	0.52186	0.22099	0.26745	0.26105
Within R^2	0.30904	0.08420	0.10014	0.09161
Mean dep. var.	257,079.7	186,111.0	232,448.1	243,449.7

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Monetary amounts are in DKK and are adjusted by CPI to 2008 level.
In the first column, the dependent variable is annual earnings in the calendar year of entering UE.
In the second column, the dependent variable is annual earnings in the calendar year after entering UE and so on.
Weighted sub-market tightness is standardised with respect to the sample standard deviation (0.30).

Table 4: Earnings in 0-3 years after UE entry and tightness at UE entry

enter UE more than once in the period. In the previous subsection, we only considered the earnings effects for workers who had found a job. Here, we look at earnings effects that are also due to slower job finding. A worker who does not have labour earnings in a particular year is coded as having zero earnings in that year. Here, we look at the annual earnings in the calendar year of entering UE. For a worker who loses his job in January or December 2012, this would in both cases be yearnings in 2012. Thus, the impact may be larger in the year after. We consider up to three years after UE entry. We have data on labour earnings throughout 2022. Thus, we do not have data for those who enter UE in 2020 in the third year after entering UE. The monetary amounts are adjusted by the CPI to 2008 levels.

The results are presented in Table 4. A standard deviation increase in tightness is associated with 9.800 kr. higher yearly earnings in the year following UE entry. The effects decrease somewhat with time but are present in the third year after UE entry where a standard deviation's increase in weighted tightness is associated with 5.865 kr. higher annual earnings. Mismatch with vacancies has persistent effects on earnings. 2SLS estimates are presented in Table A6 and the corresponding first stage in Table A5. IV estimates suggest that the effects may be even larger.[25]

The average yearly earnings in the year before job loss are 315,562 kr. If we apply the estimated effect from column 3 of Table 3 that would suggest an intensive margin effect of about 4,700 kr. That suggests that a significant part of the estimate in the year following unemployment is due to workers not having found a job. The fact that the estimate is still 5,900 kr. in the third year following UE entry point to these immediate earnings effects being persistent, as a smaller proportion of earnings in the third year is probably driven by job finding.

[25] Table B4 reports a similar table using log of weighted tightness.

5.4 Alternative results and robustness

5.4.1 Alternative measures

Our main measure of weighted tightness uses the three month averages of vacancy and unemployment count centred in the unemployment start month. Using vacancies in the unemployment start month only, alternatively, the unemployment start quarter or a five month average yields similar results as Table A7 reports.

In Section 3, alternative weighting schemes with respect to occupational relatedness were presented. The table additionally presents results with tightness measures using the origin occupation tightness only and alternative weighting schemes using O*NET measures of occupational relatedness. Using the origin occupation tightness only – or using only tightness in related occupations but excluding the origin occupations – both yield similar estimates. Using the vacancy unemployment counts in the clusters (without any weighting) gives a lower estimate (by a third). However, the O*NET weighted tightness gives almost exactly the same estimate as the transition-based weighted tightness. Compared to the cluster-based measure, the weighting by relatedness seems to matter. In that light, it is a healthy sign that the transition-based and the O*NET weighting schemes give the same results. Table A8 shows that the results are similar regarding job finding as well. The O*net weights give a slightly lower but similar estimate in this case. Table B5 and Table B6 report similar tables for a log specification with similar conclusions.

5.4.2 Instrument

Table A9 and Table A10 report the first and second stage, respectively, of a regression of immediate earnings change on weighted tightness with alternative versions of the instrument. Using the mass layoff count not conditional on taking up UI entry gives a somewhat larger IV-estimate. The table also reports results using the origin occupation mass layoff only (not using the same weighting scheme as weighted tightness). This gives a similar IV estimate. The table reports the estimation results using the weighted mass layoffs in related occupations (but excluding the origin occupation). Also, giving a similar IV estimate. Perhaps that version giving a similar estimate alleviates some concerns regarding exclusion restriction violations, for example through a local productivity shock like previously discussed. Table A11 and Table A12 report the corresponding results for the job-finding results, finding similar results across alternative versions of the instruments.

5.4.3 Quarter fixed effects

One threat to the IV strategy would be if due to a productivity shock there are more mass layoffs and earnings are also lower because productivity is lower. Similarly, if workers spend longer time in unemployment due to low productivity. Table A13 reports estimation results with unemployment start quarter fixed effects. Since we are now comparing individuals within unemployment start quarter, additionally included pre-occupation fixed effects leaves us with very limited variation in the treatment. To have a good first stage, here we use a version of the instrument where occupation means are not subtracted. To relieve the concern that there may be systematic differences in the use of mass layoffs by occupations, we include detailed pre-industry fixed effects (127 industries). That is, because that difference would most plausibly stem from the fact that the occupations are employed in different industries.

The IV estimate is similar and even slightly larger compared to the estimates reported in Table 3. If the previously reported results were largely effected by productivity shocks in the aggregate, one would expect the estimated effects to be smaller including the unemployment start-quarter fixed effects. The OLS estimates with pre-industry and unemployment start-quarter fixed effects are also reported in comparison. These estimates are similar to those reported in Table 3 even slightly larger. Table A14 reports similar results for job-finding in three months. The IV estimate is similar to that previously reported in Table 2. However, a remaining concern may be local productivity shocks occurring in certain industry-region combinations or industry-occupation-region combinations.

5.5 Heterogeneity

We find evidence of heterogeneity in the results that are consistent with what has previously been documented in the literature (see e.g., Athey et al., 2023). Table A15 shows that the effects on 3-month job finding and immediate earnings change are larger for workers older than 50 years.[26] Table A16 shows that the effects are also somewhat larger for workers without university education (without a bachelor's degree or higher). These results suggest that these groups may be particularly vulnerable to slack sub-market conditions.

5.6 Occupational mobility

Mismatch with vacancies may push workers to relocate to other occupations. This section analyses whether mismatched workers are more likely to switch occupations. Furthermore, if those who transition to another occupation travel further distance in the skill space or are more likely to move downward in the occupational rank according to the measures presented in subsection 3.1.

Table 5 reports estimation results of a regression of an indicator of switching 4 digit disco occupations, excluding transitions to a related occupations by our O*NET measure.[27] In Panel A the regressor of interest is the weighted sub-market tightness. Perhaps surprisingly, in

[26] Recall, the entire sample is below 60 years of age.

[27] I.e., to one of the top ten related occupations by the O*NET measure.

our preferred specification including the pre-occupation fixed effects, the results suggest that when tightness in a sub-market is lower, the probability of switching occupation is lower. Recall that the weighted tightness measure relies on tightness in related occupations as well, which may be a problem when analysing occupational transitions. Furthermore, when tightness is high within a given sub-market that is presumably correlated with tightness being high in other sub-markets. Column 3 reports results using unemployment start quarter fixed effects instead, using variation across occupations keeping time fixed, which shows a negative estimate. However, here we may suffer from a given level of tightness meaning different things in different occupations. And the corresponding IV estimates to not have the same sign.

To further investigate this issue, panel B reports similar results using the log of tightness in the origin occupation only. Panel C adds the log of tightness in related occupations (excluding the origin occupation) to the regression.[28] The estimates on origin occupation tightness decrease significantly. A part of the estimate may be attributed to tightness being higher in related occupations. Table A18 adds unrelated occupations to the regression, with similar results.

If tightness is high in other occupations as well, a tight sub-market may also be a good time to move upward in an occupational ladder. Table A19 reports estimation results for a regression of downward switching on weighted tightness. Firstly, an indicator of moving down in the occupation rank measured by the first principal component definition excluding moving down to related occupations (columns 1-4). Secondly, an indicator of moving downward in the cluster wage rank (columns 5-8). When tightness is lower, we expect more workers to switch downwards, by both measures. Table A20 reports 2SLS estimates that show similar estimates. However, the estimates are small compared to the sample mean. In this case, it also matters that conditions are correlated between sub-markets. The table also reports results where the dependent variable is the O*NET distance. There do not seem to be any effects of tightness on how far the switchers move in the skills space, except that tightness in unrelated occupations is negatively associated with distance travelled.

6 Job Applications by Mismatch

To examine whether workers that are mismatched with vacancies apply differently to those that match better to vacancies – and if this changes over time in unemployment – we exploit access to administrative data on applied-for jobs. From 2015, UI recipients have been required to log applications through an online system, *Joblog*. The application logs must include descriptions of the jobs applied for, including the job title and hours. Logging

[28] See Table A17 for the first stage regression.

Panel A

Dependent Variable:	Switcher to a non-related occupation (4-digit)								
	OLS						2SLS		
	Entire Sample			Displaced			Entire Sample		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Weighted Sub-Market Tightness	0.0060	0.0348***	-0.0180*	0.0312***	0.0394***	0.0102	0.0608***	0.0599***	0.0333*
	(0.0098)	(0.0031)	(0.0108)	(0.0089)	(0.0064)	(0.0119)	(0.0094)	(0.0092)	(0.0193)
Fixed-effects									
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)		Yes			Yes			Yes	
Unemployment Start Quarter			Yes			Yes			Yes
Fit statistics									
Observations	163,832	163,832	163,832	14,907	14,907	14,907	163,832	163,832	163,832
F-test (1st stage), Weighted Sub-Market Tightness							15,644.8	27,953.9	3,181.2
Mean dep. var.	0.3468	0.3468	0.3468	0.3645	0.3645	0.3645	0.3468	0.3468	0.3468

Panel B

Dependent Variable:	Switcher to a non-related occupation (4-digit)								
	OLS						2SLS		
	Entire Sample			Displaced			Entire Sample		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Log tightness (Origin Occupation Only)	0.0065	0.0451***	-0.0193*	0.0245***	0.0504***	0.0008	0.0585***	0.0586***	0.0247
	(0.0093)	(0.0037)	(0.0103)	(0.0093)	(0.0074)	(0.0110)	(0.0108)	(0.0114)	(0.0163)
Fixed-effects									
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)		Yes			Yes			Yes	
Unemployment Start Quarter			Yes			Yes			Yes
Fit statistics									
Observations	161,440	161,440	161,440	14,544	14,544	14,544	161,440	161,440	161,440
F-test (1st stage), Log tightness (Origin Occupation Only)							13,124.8	24,609.3	4,875.2
Mean dep. var.	0.3446	0.3446	0.3446	0.3634	0.3634	0.3634	0.3446	0.3446	0.3446

Panel C

Dependent Variable:	Switcher to a non-related occupation (4-digit)								
	OLS						2SLS		
	Entire Sample			Displaced			Entire Sample		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Log tightness (Origin Occupation Only)	-0.0303***	0.0138***	-0.0339***	-0.0120	0.0154	-0.0149	0.0275	0.0160	0.0518**
	(0.0110)	(0.0039)	(0.0109)	(0.0127)	(0.0110)	(0.0121)	(0.0306)	(0.0236)	(0.0263)
Log tightness in related occupations only	0.0964***	0.0538***	0.0710***	0.0870***	0.0571***	0.0676***	0.0465	0.0652***	-0.0703*
	(0.0178)	(0.0062)	(0.0254)	(0.0183)	(0.0167)	(0.0225)	(0.0336)	(0.0225)	(0.0419)
Fixed-effects									
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)		Yes			Yes			Yes	
Unemployment Start Quarter			Yes			Yes			Yes
Fit statistics									
Observations	161,440	161,440	161,440	14,544	14,544	14,544	161,440	161,440	161,440
F-test (1st stage), Log tightness (Origin Occupation Only)							13,021.3	30,205.2	2,600.5
F-test (1st stage), Log tightness in related occupations only							30,084.4	50,065.5	3,388.4
Mean dep. var.	0.3446	0.3446	0.3446	0.3634	0.3634	0.3634	0.3446	0.3446	0.3446

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Tightness and occupational switching

applications is a requirement to maintain full eligibility for unemployment insurance. Thus, UI recipients have high incentives to comply with the logging requirements. The data has previously been used and is extensively discussed in Fluchtmann et al. (2022) and Maibom et al. (2023). The data is available for a two-year period from September 2015 to September 2017.[29]

For this analysis – in particular, examining differences in the dynamics of applied-for jobs over time and decomposing the differences in outcomes by mismatch – it will prove useful to adopt a binary definition of being mismatched to vacancies. This definition will be based on the conditions in the sub-markets at the point of unemployment entry and ranking the sub-markets in the Joblog-period in terms of weighted tightness. We define the bottom quartile of sub-markets in terms of weighted tightness in the Job log period as mismatched.[30] The comparison group will be upper two quartiles (3rd and 4th) of sub-markets in terms of weighted tightness (henceforth: "well-matched").[31] The comparison group will therefore consist of workers relatively better matched to vacancies. Although we define treatment differently from before, the insights from earlier still apply. Table A21 shows that if we define being *mismatched* in a similar way for the whole period, on average mismatched workers have 3% higher earnings penalties and a 4 percentage point lower probability of finding a job in three months, compared to well-matched workers, keeping other factors fixed.

6.1 Applications over the UE spell

We begin by asking if workers alter their application behaviour over the unemployed differently than "well-matched" workers over the unemployment spell. Firstly, it may be the case that workers do not initially realise to what extent they are mismatched. In that case, we would expect larger differences in applied for jobs over the UE spell by mismatch status. Secondly, as the model of Huckfeldt (2022) would suggest, it could be the case that mismatched workers quickly internalise job-finding conditions in their sub-market and direct their applications elsewhere.

As highlighted in Maibom et al. (2023) analysis of the dynamics of job application is likely plagued by dynamic selection. For example, those who persistently apply for unrelated jobs are likely to take up a larger part of the unemployment pool over time. We thus adopt

[29] Henceforth, we will refer to that as the "Joblog-period"

[30] We pool together monthly observations for all submarkets in the Joblog-period. 144 submarkets x 25 months = 3600 submarket-month observations. The bottom 25% of these submarket-month observations in terms of weighted tightness are *mismatched*. Those individuals, that match on the submarket and the unemployment start month, are said to be in mismatch unemployment.

[31] Note, that the definition depends on the quartiles of sub-markets, not the sample of analysis. For example, less than half of the sample is defined as "well matched" while more than $\frac{1}{4}$ may be mismatched.

the same fixed effects regression specification:

$$y_{it} = \alpha_i + \tau_t + \epsilon_{it} \tag{3}$$

Where α_i are individual fixed effects and y_{it} denotes the application-outcome of interest. We are interested in the estimates on $\tau_1, ..., \tau_{12}$, the spell month fixed effects. We consider applications the first year 12 months of the UE-spell. We estimate (3) separately for mismatched (bottom tightness quartile in the period) and "well-matched" (two upper tightness quartiles in the Job-log period). For this analysis, we use only those where we have non-missing application outcomes for more than one month. The sample of analysis consists of 9,935 mismatched and 12,823 "well-matched" workers.

Estimation results of regression equation (3) are presented in Figure 3. The figure shows the estimates on the spell month dummies along with a 95% confidence interval. The estimates are shifted up by the first month average applications for mismatched and well-matched workers. As we are especially interested in comparing changes over time in unemployment, Figure C1 in Appendix C shows the estimation results of (3) directly (i.e. not shifted up by the first month average), so it is easier to compare changes over time in unemployment.[32]

Figure 3a shows the log average applied for wages over time in unemployment for mismatched and well-matched workers.[33] In the first month of unemployment, mismatched workers apply for jobs with 9.2% lower wages on average. Over time in UE, all workers apply for lower wage jobs, as Figure C1a shows. This adjustment over time does not differ significantly by mismatch status. Similar is true for the share of applications made to a related occupation (Figure 3b). In the first month of UE, the share of application made to a related occupation (O*NET definition) is 14 percentage points lower for mismatched workers. Mismatched workers direct their applications to different sub-market to a greater extent. This share declines for all workers over time in UE, that is similarly for mismatched and non-mismatched workers.

An important dimension may be the rank of the firm in terms of firm-specific wage premia.[34] Figure 3c shows the applied for firm, as measured by a firm fixed effect from an AKM regression.[35] On average, mismatched workers apply to firm that stand lower

[32]The data on wage predictions of applied for jobs, the applied for firm fixed effect, estimated commuting time and share of applications to a related industry are from Fluchtmann et al. (2022) and Maibom et al. (2023).

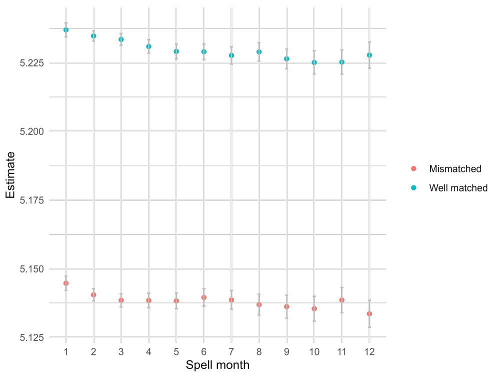
[33]The wages for the applied jobs are not observed. Therefore, this is the average predicted wage based on the realised wages of new hires. Predictions are made based on observable characteristics of the job, including its occupation and employer firm fixed effect from an AKM model (Abowd et al., 1999). See Maibom et al. (2023) Online Appendix A.4 for further information.

[34]Its importance for earnings loss following job loss is highlighted, e.g., by Bertheau et al. (2023)

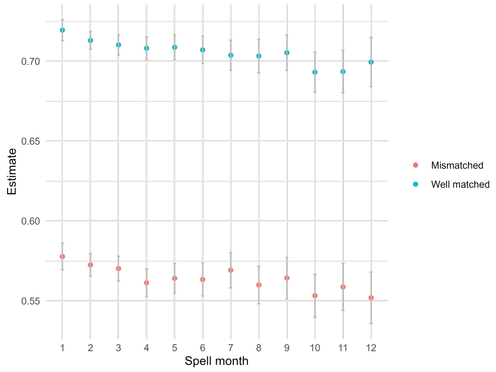
[35]The firm fixed effect is standardised by the industry standard deviation to reflect within industry differences of applied for firms.

Figure 3: Applications over the unemployment spell by mismatch

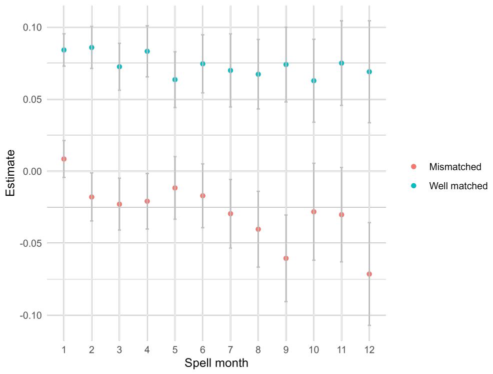
Estimation results of regression equation (3). The figure shows estimates on spell month dummies for mismatched workers (red line) and non-mismatched workers (blue line). 95% confidence intervals are shown, standard errors are clustered at the individual level. The estimates shifted up by the first month mean.



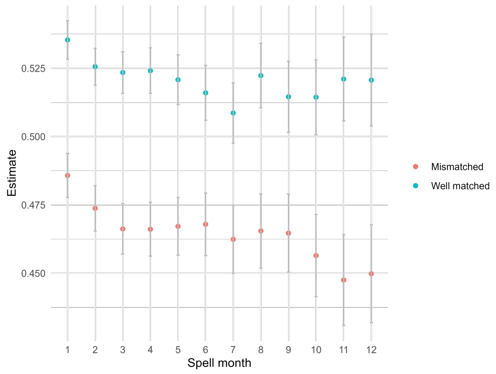
(a) Applied for wages over time in UE.



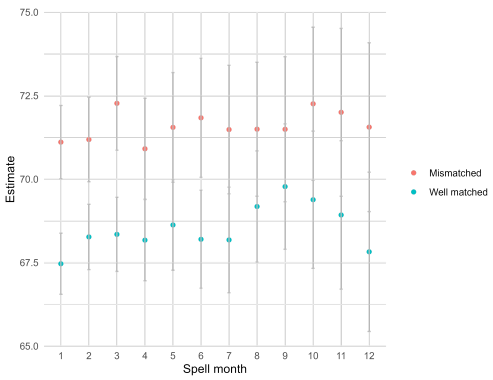
(b) Share of application to a related occupation.



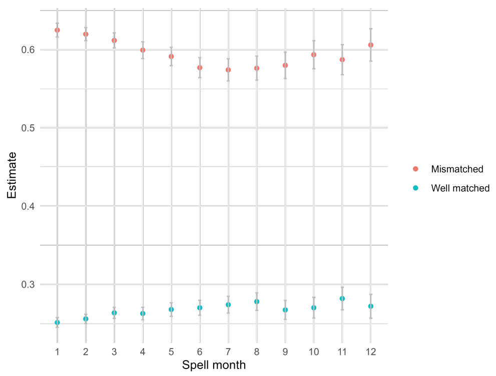
(c) Applied for firm.



(d) Share of applications to a related industry.



(e) Applied for commuting time.



(f) Share of applications to a tighter labour market.

in the firm rank. There is a limited change over time in unemployment for both groups (Figure C1c). Figure 3d presents further evidence that mismatched workers search more broadly. Their share of application to a related industry is somewhat higher on average, although the difference is not as large compared to the share of applications to a related occupation.[36] Similar to the share of applications to related occupations, the share directed to a related industry goes down for all workers over time in unemployment, but similarly for mismatched and well-matched workers.

Another relevant dimension may be commute time. Figure 3e shows the average commute time applied for, between home and work, over time in unemployment. Commute times are estimated driving times, accounting for congestion, between the centroid of the residence municipality worker and the zip code of the establishment applied for. There is a small initial difference in average commute time applied for by mismatch status, but limited change over time in unemployment.

Mismatched workers direct a much larger share of their application to a tighter sub-market, namely 62% (Figure 3f). While, well-matched worker direct 22% share of their first-month applications to a tighter sub-market. From the first month onwards, the mismatched workers are entering shorter queues relative to their origin sub-market. Figure C1f suggests that this goes down for mismatched workers as time in unemployment grows. That may, at least in large part, be accounted for by more favourable conditions in the origin sub-market as time in unemployment grows (see Figure C2f).

Figure C2 presents estimation results of (3) for additional application outcomes. In particular, an the share of application to a downward transition in the occupational rank and the O*NET distance applied for (subsection 3.1 presents these measures). Interestingly, although we have documented that mismatched workers conduct a broader search, a slightly lower share of application made to a downwards occupational transition (except measured by principal component 3, "math and programming skills", where the share is substantially higher for mismatched workers). The average distance of occupation applied for is also slightly lower for mismatched workers. However, these differences are small compared to the mean. For all workers, the share of applications made to a downwards occupation grows somewhat over time time in UE, as Figure C3 shows.

For the outcomes considered, we document similar adjustment in application behaviour over time for mismatched and well-matched workers. From the first month of unemployment mismatched workers apply differently from well-matched workers and that difference is stable over time in unemployment.

[36] Related industry is defined by what transitions are frequently observed in the data. For further details, see Maibom et al. (2023) section 3.3 and Appendices B4 and B5.

6.2 First-month Applications and Post-UE Outcomes

We have documented that there are limited differences in the way that mismatched and well-matched workers adjust their application strategies over time in unemployment. The results presented in the previous sub-section suggest that there are initial differences, sometimes substantial, in the way that mismatched and well-matched workers direct their applications. In this section, we investigate these initial differences in some of the main application outcomes in further detail. Firstly, by adding controls for other factors that could correlate with mismatch status and the application outcomes. Secondly, using a more credible identifying variation by instrumenting the indicator of being mismatched by mass layoffs of others in the same sub-market.

Another goal of this section is to contrast the differences in applications outcomes with the outcomes regarding the post-unemployment job. That is, to contrast how the effects of mismatch realise on the application margin to the hiring margin. Therefore, here we analyse the sub-sample that gets a post-job. In essence, the empirical strategy is similar to what is described in section 4 with three differences. Firstly, treatment is defined by the binary definition, that is, the submarket of entry is in the bottom tightness quartile. And the comparison group consits of the workers that belong to the upper two quartiles of sub-markets. Seccondly, pre-occupation fixed effects are subsituted by pre-industry fixed effects. Recall that the inclusion of pre-UE occupation fixed effects limits the treatment variation by more than half in the whole period. Here, we only have two years, and variation of tightness within occupation is even more limited. The inclusion of pre-UE occupation fixed shuts down more than 70% of treatment variation. Instead we substitute them with pre-industry fixed effects that should hold fixed some of the factors we would like to keep fixed using the pre-occupation fixed effects. Such as the role of informal hiring channels, etc.

The third difference concerns the instrument. Previously, we used mass layoffs of others in the same sub-market in the same month after subtracting the occupation mean in the sample period. With the binary treatment definition in this two-year period we have a better first stage using the count of mass-layoffs of others in the same sub-market in the same month without subtracting occupation means. But note that we use them here in combination with pre-industry fixed effects, which account for the fact that some occupations are employed in industries that use mass layoffs to a greater extent.

We consider three sets of outcomes, i.e. three combinations of a application outcome and a post-UE outcome. Regression estimation results are presented in Table 6. The number of observations differs slightly between sets of outcomes due to the requirement that the application outcome in each set is non-missing. The first set of outcomes considered are applied for log wages and log wages in the post-unemployment job. The first column reports that mismatched workers apply for jobs with 3% lower wages on average, keeping other factors fixed. Similarly, wages in the post-unemployment job are 4% lower on average compared to well-matched workers (column 2). The third column shows the first stage for the two-stage least-squares estimation. The fourth and fifth columns show the 2SLS estimates. For both applied for wages and wages in the post-UE job, the IV results suggest that the effects of mismatch may be even higher.

Regarding the applied for firm fixed effects, the OLS estimates suggest that mismatch workers apply for and are hired to firms that stand lower in the firm rank. For the average applied for firm, the IV estimate is similar, but regarding the post-UE firm the IV estimate has a different sign. However, neither is statistically significant.

Mismatched workers direct a lower share of applications to related occupations. Namely, 10 percentage points lower share according to the OLS-estimate. The IV estimate is slightly lower (6 pp) but is imprecisely estimated. However, we do not observe similar results for the post-unemployment job. The OLS estimate does not show any difference in whether mismatched and well-matched workers end up in a related occupation, and the IV estimate suggests that this share may be higher for mismatched workers, although the estimate is only statistically significant at the 10% level.

7 Decomposition

This paper has documented that workers who are mismatched with vacancies find a job slower and suffer larger earnings losses. Furthermore, the previous section documented that mismatched workers apply differently from the first month of unemployment onwards. In particular, they apply for lower-wage jobs and conduct a broader job search, with a larger share of applications directed to non-related occupations. However, mismatched workers are not observed transiting to non-related occupations to a greater extent. This may indicate that they do not have luck in accordance at the hiring margin. These workers may be broadening their search sub-optimally, leading to even worse outcomes. Thus, a natural question is whether mismatched workers search differently in such a way as to alleviate adverse outcomes? In an attempt to answer this, we rely on counterfactual job-finding probabilites for mismatched workers if they had similar application behaviour as well-matched. These counterfactual probabilities are used to decompose the gap in job finding probabilities between mismatched and well-matched workers, after correcting for observable characteristics, into a part that can be explained by differences in application behaviour and a residual part.

7.1 Set up

The application of a two-step DiNardo et al. (1995) decomposition to job applications follows Fluchtmann et al. (2022). The first step involves estimating the gap in outcomes between

Dependent Variables:	Applied for wages	Wages post UE job	Mismatched	Applied for wages	Wages post UE job
IV stages	OLS	OLS	First	Second	Second
Model:	(1)	(2)	(3)	(4)	(6)
Variables					
Mismatched	-0.0302***	-0.0407***		-0.1042***	-0.0759***
	(0.0053)	(0.0077)		(0.0293)	(0.0253)
Log Pre Wage	0.1349***	0.3932***	-0.2512***	0.1144***	0.3834***
	(0.0053)	(0.0168)	(0.0459)	(0.0109)	(0.0176)
Mass layoffs to population (weighted)			46,601.4***		
			(12,913.7)		
Fit statistics					
Observations	15,171	15,171	15,171	15,171	15,171
F-test (1st stage)			792.44		
Dependent Variables:	Applied for FFE	Post-UE FFE	Mismatched	Applied for FFE	Post-UE FFE
IV stages	OLS	OLS	First	Second	Second
Model:	(1)	(2)	(3)	(4)	(6)
Variables					
Mismatched	-0.0359**	-0.0600***		-0.0221	0.0737
	(0.0158)	(0.0171)		(0.0462)	(0.1004)
Pre-UE FFE	0.0722***	0.1271***	-0.0054	0.0722***	0.1275***
	(0.0091)	(0.0102)	(0.0128)	(0.0091)	(0.0107)
Mass layoffs to population (weighted)			49,480.9***		
			(13,508.7)		
Fit statistics					
Observations	14,578	14,578	14,578	14,578	14,578
F-test (1st stage)			864.34		
Dependent Variables:	Appl.to Related Occ. (share)	Post UE in related occ. (indicator)	Mismatched	Appl.to Related Occ. (share)	Post UE in related occ. (indicator)
IV stages	OLS	OLS	First	Second	Second
Model:	(1)	(2)	(3)	(4)	(6)
Variables					
Mismatched	-0.1040***	0.0029		-0.0609	0.1373*
	(0.0263)	(0.0143)		(0.0592)	(0.0729)
Log Pre Wage	0.0603**	-0.0166	-0.2641***	0.0729**	0.0227
	(0.0262)	(0.0220)	(0.0421)	(0.0306)	(0.0318)
Mass layoffs to population (weighted)			46,873.5***		
			(12,910.1)		
Fit statistics					
Observations	16,274	16,274	16,274	16,274	16,274
F-test (1st stage)			875.39		
Fixed-effects					
Age	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes
Level of Education	Yes	Yes	Yes	Yes	Yes
Commute area	Yes	Yes	Yes	Yes	Yes
Pre-UE industry	Yes	Yes	Yes	Yes	Yes

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Note: The top panel of the table considers average applied for wages in the first month of unemployment and wages in the post-unemployment job. The middle panel considers the average applied-for firm fixed effect in the first month of unemployment and the fixed effect of the post-UE firm. The firm fixed effect is standardised with the industry standard deviation to reflect within industry differences.
The bottom panel considers the share of application to a related application in the first month of unemployment and an indicator of whether the post-unemployment job is in a related occupation.

Table 6: First month applications, post-UE outcomes and mismatch

mismatched and well-matched workers if they had the same distribution of observable characteristics ("baseline gap"). The second step decomposes this baseline gap to a part that can be explained by differences in application behaviour and a residual. This involves estimating the hiring probability that mismatched workers would have faced if they had the same distribution of observables and the same application behaviour as the well-matched workers.

Let $P^{MM}(y)$ be the probability that a mismatched worker (superscript "MM") finds a job in 3 months. Similarly, let $P^{MM}(y \mid \boldsymbol{a}, \boldsymbol{x})$ denote the probability that a mismatched worker finds a job in 3 months conditional on observable characteristics $\boldsymbol{x}$ and applications $\boldsymbol{a}$. We have that:

$$P^{MM}(y) = \iint P^{MM}(y \mid \boldsymbol{a}, \boldsymbol{x}) f^{MM}_{a|x}(\boldsymbol{a} \mid \boldsymbol{x}) f^{MM}_{x}(\boldsymbol{x}) d\boldsymbol{a} d\boldsymbol{x} \tag{4}$$

where f^{MM}_{x} is the distribution of observable characteristics for mismatched workers and $f^{MM}_{a|x}(\boldsymbol{a} \mid \boldsymbol{x})$ is the conditional distribution of applications conditioned on observable characteristics.

Let the superscript "WM" denote the corresponding quantities for well-matched workers (i.e., the upper two quartiles in terms of sub-market tightness in the job log period). We can construct the counterfactual probability that a mismatched worker finds a job in 3 months if they had the same distribution of observable characteristics as a non-mismatched worker as:

$$\widetilde{P^{MM}_{\boldsymbol{x}}(y)} = \iint P^{MM}(y \mid \boldsymbol{a}, \boldsymbol{x}) f^{MM}_{a|x}(\boldsymbol{a} \mid \boldsymbol{x}) f^{WM}_{x}(\boldsymbol{x}) d\boldsymbol{a} d\boldsymbol{x} \tag{5}$$

Now we can construct the gap if well matched workers had the same distribution of observable characteristics as mismatched workers as:

$$\widetilde{P^{MM}_{\boldsymbol{x}}(y)} - P^{WM}(y) \tag{6}$$

which is what Fluchtmann et al. (2022) refer to as the "baseline gap" and will be the object of decomposition. $\widetilde{P^{MM}_{\boldsymbol{x}}(y)}$ is estimated by propensity score re-weighting the mismatched to have the same characteristics as the well matched workers and computing the share finding a job in three months. The propensity scores are estimated by a logit model. Here we select similar characteristics to the controls in the previous subsection, namely: age, age squared, gender, level of education, pre-unemployment industry, commuting zone and pre-unemployment earnings in logs.

Next, we construct the counterfactual job finding probability if mismatched workers applied in the same manner as non-mismatched workers (and had the same distribution of observables):

$$\widetilde{P^{MM}_{\boldsymbol{x},\boldsymbol{a}}(y)} = \iint P^{MM}(y \mid \boldsymbol{a}, \boldsymbol{x}) f^{WM}_{\boldsymbol{a}|x}(\boldsymbol{a} \mid \boldsymbol{x}) f^{WM}_{x}(\boldsymbol{x}) d\boldsymbol{a} d\boldsymbol{x} \tag{7}$$

$\widetilde{P^{MM}_{\boldsymbol{x},\boldsymbol{a}}(y)}$ may be estimated by propensity score reweighting the sample of mismatched to have the same distribution of observables and application behaviour as the well matched. Here $\boldsymbol{a}$ consits the first month application outcomes presented in the previous section. Namely, the share of applications in a relation occupation, the share of applications in a related occupation, the share of application to a tighter sub-market, applied for log-wages, applied for firm fixed effect, average applied-for commuting time, share of applications to a downward occupation measured by principal components 1 and 3. Propensity scores are estimated using a logit model.[37] Now we can write:

$$\underbrace{\widetilde{P^{MM}_{\boldsymbol{x}}(y)} - P^{WM}(y)}_{\text{baseline gap}} = \underbrace{\left[\widetilde{P^{MM}_{\boldsymbol{x}}(y)} - \widetilde{P^{MM}_{\boldsymbol{x},\boldsymbol{a}}(y)}\right]}_{\text{explained by applications}} + \underbrace{\left[\widetilde{P^{MM}_{\boldsymbol{x},\boldsymbol{a}}(y)} - P^{WM}(y)\right]}_{\text{residual}} \tag{8}$$

Lastly, we apply the decomposition to another key outcome in the paper, immediate earnings difference. Let $P^{MM}_{\boldsymbol{x}}(y)$ denote the probability that a mismatched worker finds a post-unemployment job with immediate earnings change $IEC(y)$. Then we have:

$$\begin{aligned} &\underbrace{\sum_y IEC(y)\widetilde{P^{MM}_{\boldsymbol{x}}(y)} - \sum_y IEC(y)P^{WM}(y)}_{\text{baseline gap}} \\ = &\underbrace{\sum_y IEC(y)\left[\widetilde{P^{MM}_{\boldsymbol{x}}(y)} - \widetilde{P^{MM}_{\boldsymbol{x},\boldsymbol{a}}(y)}\right]}_{\text{explained by applications}} + \underbrace{\sum_y IEC(y)\left[\widetilde{P^{MM}_{\boldsymbol{x},\boldsymbol{a}}(y)} - P^{WM}(y)\right]}_{\text{residual}} \end{aligned} \tag{9}$$

7.2 Decomposition results

In the set up above, the probability of a mismatched worker finding a job in 3 month $P^{MM}(y \mid \boldsymbol{a}, \boldsymbol{x})$ depends on application behaviour $\boldsymbol{a}$ and a set of observables $\boldsymbol{x}$. The implicit assumption is that un-modeled factors or unobserved factors that affect hiring probabilities are independent of applications, conditional on the included observables. If a mismatched worker were to start direct a similar share of applications to a related occupation as the well-matched workers, we assume that she faces similar job finding outcomes as mismatched workers that already apply in such a manner and have similar observable characteristics.

The concern is that mismatched workers that apply like well-matched differ among non-captured factors that affect job finding outcomes. A particular example may be that mismtached workers that apply like well-matched workers may be less observant of conditions in their sub-market. Which may be a sign of a worse search effort or efficiency that may also

[37]We follow the same trimming procedure for the propensity scores as in Fluchtmann et al. (2022). That is, observations are trimmed where the estimated propensity score is over 0.99 or below 0.01.

mean they are less efficient or put less effort at finding jobs to target for which they would be a good match. Even though concerns like this may be valid, the decomposition exercise is still useful to explore if differences in application behaviour alleviate or amplify the effects of being mismatched.

Table 7 presents the decomposition results. Here we require the set of application variables to be non-missing. For the decomposition of the job-finding outcomes, the sample consists of 19,166 individuals thereof 7,629 mismatched. For the immediate earnings change, we use the sample that gets a post-unemployment job (within some time period, see section 2). Counting 13,928 observations, thereof 5,448 mismatched workers. Standard errors are obtained by bootstrapping. We follow a similar bootstrapping procedure as Fluchtmann et al. (2022). That is, we create 2,000 bootstrap samples by resampling unemployment spells. Within each bootstrap the propensity scores are re-estimated and the counterfactual gaps between mismatched and well-matched are re-estimated.

Outcome variable	Gap accounting for observables	Explained by applications	Residual
Finds a job in 3 months	-0.060 (0.012)	-0.038 (0.017)	-0.022 (0.021)
Finds a job in 6 months	-0.038 (0.017)	-0.042 (0.020)	0.004 (0.024)
Earnings difference (pre - post)	-0.061 (0.011)	-0.033 (0.014)	-0.028 (0.016)

Table 7: Decomposition Results.
The table reports decomposition results of a DFL decomposition of the gap in outcomes for mismatched and well-matched workers. Standard errors are obtained by bootstrapping. For job finding outcomes, the sample consists of 19,166 individuals thereof 7,629 mismatched. For immediate earnings difference the sample consists 13,928 observations, thereof 5,448 mismatched workers.

First, consider the probability of finding a job in 3 months. Mismatched workers have a 6.0 percentage point lower probability of finding a job in 3 months compared to well-matched workers after correcting for differences on observable characteristics. A large part of that gap (about $\frac{2}{3}$) can be explained by differences in applications. If we consider job finding in 6 months, mismatched workers have a 0.038 lower probability of finding a job in 6 months after accounting for differences in observables. That difference can be more than entirely explained by differences in application behaviour. The residual, which is the estimate of the counterfactual gap in outcomes if mismatched workers both had the same observable characteristics and application behaviour is slightly positive. The gap in job-finding outcomes may be largely or entirely explained by differences in applications behaviour. Note that the part explained by applications is negative if

$$\widetilde{P_{\boldsymbol{x}}^{MM}(y)} < \widetilde{P_{\boldsymbol{x},\boldsymbol{a}}^{MM}(y)}$$

I.e. if the probability that a mismatched worker, with similar characteristics as a well matched worker, finds a job in 3 months is less than the counterfactual probability that a mismatched worker finds a job in 3 months applied as she were well matched. This counterfactual probability is in all cases higher according to Table 7. It does not appear that mismatched workers apply differently in a way that produces more favourable job-finding outcomes.

The gap in immediate earnings difference after accounting for observables is about 6.0 percentage points. Approximately half of that may be explained by differences in application behaviour. The counterfactual gap that would remain if mismatched workers applied as well matched workers and had similar observable characteristics is -0.028. By itself, it is not surprising that a large part of the earnings difference can be explained by mismatched workers applying for less related and lower-wage jobs. Combined with the fact that the differences in application behaviour do not seem to translate into faster job-finding suggests that the different application behaviour of mismatched workers may in fact not be improving their outcomes.

8 Conclusion

This paper examines the importance of mismatch with vacancies for unemployment and post-unemployment outcomes of unemployed job seekers. We build measures of occupational relatedness that, combined with data on vacancies and unemployment in a segmented labour market, are used to build measures of how well unemployed workers match with vacancies. These measures are used to quantify the impacts of mismatch with vacancies on job-finding, post-unemployment earnings, and occupational relocation outcomes for unemployed workers. Although, we do not solve all potential problems regarding estimating the effects of mismatch, using alternative identification strategies and through a series of robustness checks, we show that there is a strong signal in our estimates.

Ex ante, it is not clear whether mismatch with vacancies matters more for length of the unemployment spell or earnings. We provide evidence that mismatch to vacancies is important for both margins. In terms of size, compared to the sample mean, the estimated impact is similar when looking at job finding in 3 months and immediate earnings difference. Moreover, we provide evidence that the effects on earnings are persistently present three years after unemployment entry. Surprisingly, we do not find evidence that more mismatched workers are more likely to switch occupations. However, we find some evidence that mismatched switchers are more likely to switch downward in occupational rank.

Next, we examine differences in job application behaviour between mismatched workers and those that match better with vacancies. We document that mismatched workers direct their applications to lower wage jobs on average and conduct a broader search; in particular, they direct more applications to non-related occupations. The adjustment in application strategies over time in unemployment in similar for mismatched workers and the comparison group.

We document a discrepancy between the fact that mismatched workers direct a larger share of their applications to non-related occupations and that they are nonetheless not more likely to end up in related occupations. We pose the question whether mismatched workers are searching in a way that alleviates the effects of being mismatched. In an attempt to examine this, we apply a decomposition exercise based on counterfactual job-finding probabilities if mismatched workers applied in a similar manner as the comparison group. The results do not indicate that mismatched workers apply differently in a way that speeds up job finding. Suggesting that they may be to a larger extent targeting non-related jobs in which they have a small probability of being hired. This may have implications for policy. In particular, a measurement of mismatch with vacancies may be useful metric to effectively target workers in need of job search assistance.

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A Additional Results and Robustness

Table A1: Descriptive statistics

	Entire Sample	Displaced
	N = 237,038[1]	**N = 21,630**[1]
Characteristics		
Female	114,338 (48%)	9,789 (45%)
Age at Unemployment Start	44 (9)	45 (9)
Married or Registered Partnership	110,491 (47%)	10,705 (49%)
Persons in Household	2.76 (1.31)	2.75 (1.30)
Years of Education	14.43 (2.41)	14.07 (2.42)
Years Since Completeion of Highest Education	20 (11)	21 (11)
Level of Education		
Primary	619 (0.3%)	80 (0.4%)
Lower secondary	39,286 (17%)	4,432 (20%)
Upper secondary	115,425 (49%)	11,094 (51%)
Short cycle tertiary	15,017 (6.3%)	1,327 (6.1%)
Bachelor or equivalent	41,689 (18%)	2,896 (13%)
Master or equivalent	23,425 (9.9%)	1,682 (7.8%)
Doctoral or equivalent	1,577 (0.7%)	119 (0.6%)
Pre-Unemployment Job		
Average Earnings per Month over Jobspell [Kr.]	27,521 (11,486)	27,874 (11,020)
Average Hours per Month over Jobspell	145 (19)	149 (17)
Average Hourly Wage over Jobspell [Kr.]	188 (70)	187 (67)
Average Pre-Spell Duration [Months]	31 (27)	37 (26)
Unemployment		
Unemployment Duration [Weeks]	26 (23)	27 (24)
Finds a Job Within 3 Months	62,968 (27%)	5,734 (27%)
Finds a Job Within 6 Months	113,309 (48%)	10,205 (47%)
Finds a Job Within 9 Months	140,718 (59%)	12,725 (59%)
Finds a Job Within 12 Months	158,007 (67%)	14,309 (66%)
Finds a Job Within 15 Months	170,606 (72%)	15,455 (71%)
Finds a Job Within 18 Months	180,311 (76%)	16,378 (76%)

[1]n (%); Mean (SD)
Note: Monetary amounts are adjusted for inflation by a CPI index since 2008.

Table A2: Descriptive statistics on the post-UE job spell

	Re-Employed Sample	Displaced
	N = 163,832[1]	**N = 14,907**[1]
Post-Unemployment Job		
Average Earnings per Month over Jobspell [Kr.]	24,641 (10,926)	24,401 (10,493)
Average Hours per Month over Jobspell	134 (30)	135 (30)
Average Hourly Wage over Jobspell [Kr.]	182 (64)	179 (61)
Post-Spell Duration [Months]	22 (24)	24 (27)
Comparison of Spells		
Immediate Earnings Differences (post minus pre in logs)	-0.15 (0.28)	-0.18 (0.29)
Immediate Hours Differences (post minus pre in logs)	-0.06 (0.20)	-0.06 (0.20)
Immediate Wage Differences (post minus pre in logs)	-0.09 (0.21)	-0.11 (0.22)

[1]Mean (SD)
Note: Monetary amounts are adjusted for inflation by a CPI index since 2008.
Immediate earnings difference is the log of average monthly earnings in the first month of the pre-UE job and the log of average monthly earnings in the post-unemployment job.
Immediate hour and wage difference is defined in a similar manner.

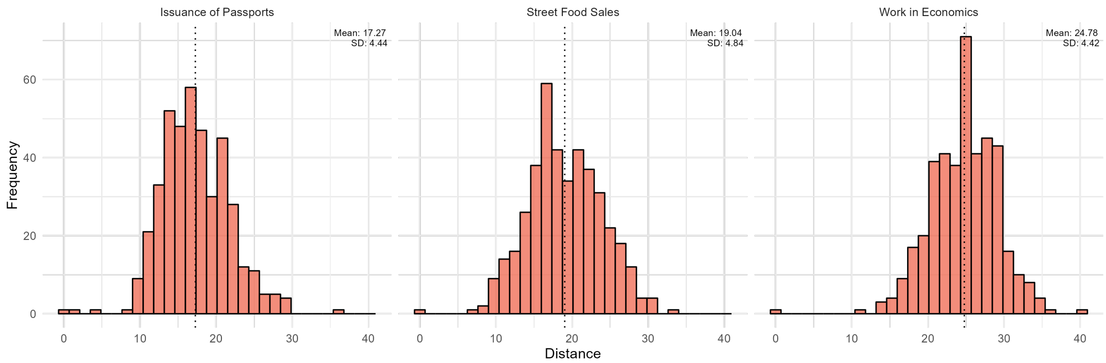


Figure A1: The distribution of distance to other occupations by the O*NET measure.
Note: The figure shows the distribution of O*NET distance for three origin occupations to all potential 4-digit DISCO destination occupations.

Most Related		Least Related	
DISCO Code	Title	DISCO Code	Title
Work in Economics (2631)			
2120	Work with mathematical, actuarial and statistical methods and theories	9121	Manual washing and pressing of clothes
3314	Work with statistics and mathematics	5153	Property inspector work
2633	Work in philosophy	9123	Window cleaning
2413	Work with analysis	8152	Operator work in weaving and knitting
1211	Management in finance functions	8172	Operator work in wood processing
2411	Audit and accounting controller work	7523	Operator and erection work of woodworking machines
2632	Work in sociology	9612	Work with waste sorting
3339	Other work in business services	9111	Cleaning work in private homes
2310	Teaching and research at universities and colleges	8153	Operator work of sewing machines
2519	Other work with software	9112	Cleaning work except in private homes
Issuance of passports (3354)			
3353	Provision of public services	9121	Manual washing and pressing of clothes
3351	Customs and border guards work	7523	Operator and erection work of woodworking machines
3315	Assessment and assessment work	8172	Operator work in wood processing
3355	Police investigation work	8152	Operator work in weaving and knitting
2643	Translator work and other linguistic work	8153	Operator work of sewing machines
3339	Other work in business services	5244	Sales work in customer contact centers
3324	Business brokerage work	5153	Property inspector work
2422	Work with company strategy / policy	9123	Window cleaning
4221	Travel agency work	4413	Proofreading and related functions
3411	Legal work at intermediate level	7535	Skin processing
Street food sales (5212)			
5131	Waiter work	2111	Work in physics and astronomy
5142	Beautician work and related functions	1342	Management of the main activity in the field of health
5246	Cashier work in catering and fast food	1323	Management of the main activity within construction and civil engineering
5211	Stade and market sales	2161	Work with building architecture
9520	Street sales (excluding groceries)	2142	Engineering work relating to buildings and structures
5141	Hairdressing work	1345	Management of the main activity within the teaching area
9334	Work with replenishment of warehouse and store	2162	Working with landscape architecture
5230	Cashier work and related customer service	2164	Work with urban and traffic planning
4212	Bookmaker and croupier work as well as related functions	2144	Engineering work in mechanical systems
9411	Preparation of fast food	1112	Top management in public companies

Table A3: Examples of the ten most and the ten least related occupations by the O*NET distance measure

Note: The table reports the top ten most related (in descending order) and the top ten least related occupation to three selected four-digit disco occupations.

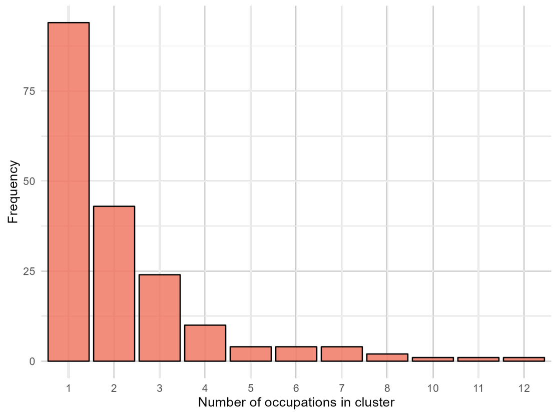


Figure A2: The number of occupation in clusters of related occupations defined by the O*NET data.
Note: The figure shows the size distribution of clusters of O*NET related occupations in terms of how many 4 digit DISCO occupations are included.

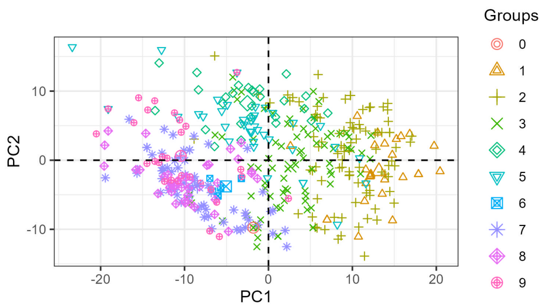


Figure A3: Occupations in terms of the first two principal components
The X-axis shows four-digit DISCO occupations in terms of the first principal component, "active learning etc." and the Y-axis shows the occupations in terms of the second principal component "service skills". The occupations are coloured by the DISCO main classification group.

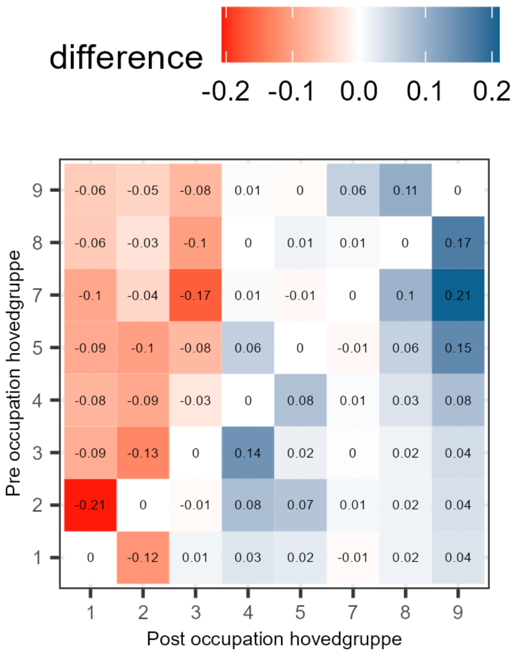


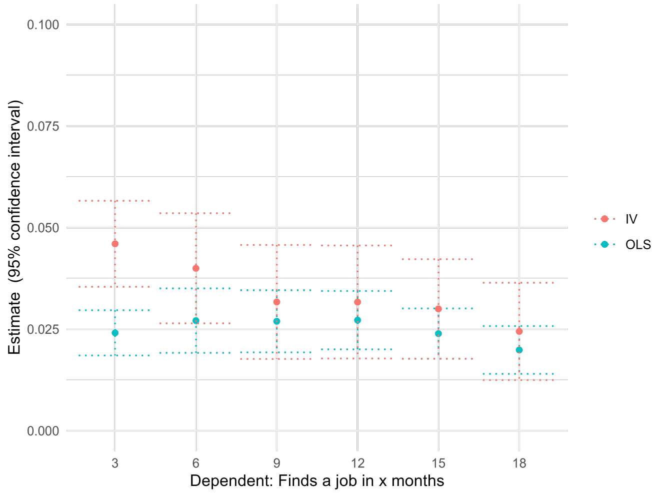
Figure A4: Comparison of Occupational Transitions of the Unemployed Sample and Direct Transitions in the labour market

I.e. employment to employment transitions and transitions with minimal stop in unemployment (less than 30 days). The figure shows a transition matrix between main occupation groups (1 digit DISCO groups) for our sample of unemployed workers after subtracting a similar transition matrix constructed from direct transitions in the labour market. For example, the probability of observing a transition from work that requires knowledge at the highest level to management is 21 percentage points lower in our sample of unemployed workers compared to direct occupational transitions in the labour market.

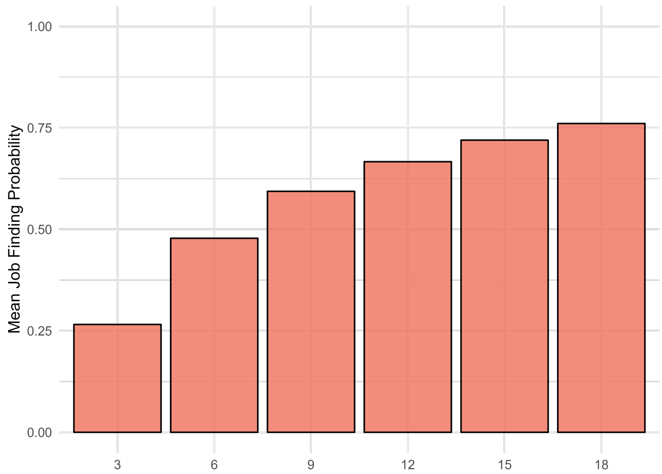
Dependent Variable:	Log Post Earnings - Log Pre Earnings				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Log Pre Earnings	-0.5206***	-0.5250***	-0.5215***	-0.5212***	-0.5295***
	(0.0120)	(0.0118)	(0.0120)	(0.0120)	(0.0119)
O*NET Distance	-0.0074***				
	(0.0029)				
Downwards Switchers (PC1 definition, excl. rel.)		-0.0532***			
		(0.0048)			
Downwards Switchers (PC2 definition, excl. rel.)			0.0243***		
			(0.0061)		
Downwards Switchers (PC3 definition, excl. rel.)				-0.0362***	
				(0.0039)	
Downwards Switcher (cluster wage rank)					-0.0761***
					(0.0042)
Fixed-effects					
Level of Education	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	163,832	163,832	163,832	163,832	163,832
R^2	0.26385	0.26791	0.26414	0.26541	0.27408
Within R^2	0.23054	0.23478	0.23084	0.23216	0.24123
Mean dep. var.	-0.1546	-0.1546	-0.1546	-0.1546	-0.1546

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: Immediate earnigns difference and switching downwards.
Note: The table reports estimation regression results where the dependent variable is the difference between the average monthly earnings in the first months of the post-UE job and the average monthly earnings in the last months of the pre-UE job. The regressors of interests are defined in subsection 3.1



(a) Estimates of the effects of tightness.



(b) Mean job finding probability.

Figure A5: Weighted tightness and job-finding.
The upper panel reports estimation results of a similar regression as in col. 3 and col.6 of Table 2. The dependent variable is an indicator of finding a job in 3, 6, 9, 12, 15, and 18 months. The lower panel shows the mean of the dependent vairable.

Table A5: First stage: Earnings in 0-3 years after UE entry

Dependent Variable:	Weighted Sub-Market Tightness	
Model:	(1)	(2)
Variables		
Mass Layoffs to Population weighted (mean dev.)	-111,759.6***	-109,152.8***
	(15,344.9)	(17,233.3)
Yearly earnings year before UE (kr.)	1.23×10^{-7}***	1.41×10^{-7}***
	(2.82×10^{-8})	(2.99×10^{-8})
Fixed-effects		
Pre-Unemployment Occupation (4 digit)	Yes	Yes
Age	Yes	Yes
Level of Education	Yes	Yes
female	Yes	Yes
Commuting Area	Yes	Yes
Fit statistics		
F-test (1st stage)	33,399.0	27,241.8

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A6: 2SLS estimation results earnings in 0-3 years after UE entry and weighted sub-market tightness

Dependent Variables:	Yearly earnings year of entering UE (kr.)	Yearly earnings 1st year after entering UE (kr.)	Yearly earnings 2nd year after entering UE (kr.)	Yearly earnings 3rd year after entering UE (kr.)
Model:	(1)	(2)	(3)	(4)
Variables				
Weighted Sub-Market Tightness	-4,010.4**	16,976.3***	11,280.7***	6,249.7***
	(1,763.9)	(1,874.2)	(2,062.3)	(2,395.8)
Yearly earnings year before UE (kr.)	0.5975***	0.3519***	0.4053***	0.4058***
	(0.0183)	(0.0144)	(0.0146)	(0.0134)
Fixed-effects				
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes
Level of Education	Yes	Yes	Yes	Yes
female	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Fit statistics				
F-test (1st stage), Weighted Sub-Market Tightness	33,399.0	33,399.0	33,399.0	27,241.8
Mean dep. var.	257,079.7	186,111.0	232,448.1	243,449.7

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Monetary amounts are in DKK and are adjusted by CPI to 2008 level.
In the first column, the dependent variable is annual earnings in the calendar year of entering UE.
In the second column, the dependent variable is annual earnings in the calendar year after entering UE and so on.
Weighted sub-market tightness is standardised with respect to the sample standard deviation (0.30).

Dependent Variable:	Log Post Earnings - Log Pre Earnings							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Weighted Sub-Market Tightness	0.0149***							
	(0.0016)							
Log Pre Earnings	-0.5211***	-0.5210***	-0.5210***	-0.5219***	-0.5215***	-0.5212***	-0.5240***	-0.5218***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0146)	(0.0122)
WST (quarter)		0.0129***						
		(0.0020)						
WST (month)			0.0145***					
			(0.0015)					
WST (5 month rolling average)				0.0150***				
				(0.0016)				
ST (3 month origin occupation only)					0.0130***			
					(0.0018)			
WST (3 month weighted, excl. own)						0.0121***		
						(0.0011)		
ST (clusters cor. dist)							0.0100***	
							(0.0026)	
WST O*NET weights								0.0151***
								(0.0021)
Fixed-effects								
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	163,832	163,832	163,832	161,838	161,440	163,832	131,742	162,803
R^2	0.26449	0.26407	0.26450	0.26535	0.26398	0.26429	0.26288	0.26463
Within R^2	0.23121	0.23077	0.23121	0.23191	0.23096	0.23100	0.23043	0.23126
Mean dep. var.	-0.1546	-0.1546	-0.1546	-0.1552	-0.1542	-0.1546	-0.1524	-0.1546

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted sub-market tightness is uses 3 month rolling average of vacancies and unemployment, and transition based weights.
WST (quarter) is weighted sub-market tightness in the unemployment start quarter, using transition based weigths.
WST (month) is weighted sub-market tightness in the unemployment start month, using transition based weigths.
WST (5 month roling average) uses a 5 month rolling average of vacancies and unemployment and transition based weights.
ST (3 month origin occupation only) uses tightness in the origin occupation only and uses 3 mo. rolling average.
WST (3 month weighted, excl. own) uses the weighted sub-market tightness in related occupations, but excludes the origin occupation.
ST (clusters cor. dist) is the unweighted tightness in O*NET defined clusters of related occupations.
WST is the weighted sub-market tightness based on the O*NET weighting scheme.
All tightness measures are standardised w.r.t. the sample standard deviation.

Table A7: Immediate earnings difference and alternative tightness measures.

Table A8: Job finding in 3 months and alternative tightness measures

Dependent Variable:	Finds a Job Within 3 Months (indicator)							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Weighted Sub-Market Tightness	0.0241***							
	(0.0028)							
WST (quarter)		0.0237***						
		(0.0029)						
WST (month)			0.0219***					
			(0.0025)					
WST (5 month rolling average)				0.0265***				
				(0.0031)				
ST (3 month own occupation only)					0.0191***			
					(0.0030)			
WST (3 month weighted, excl. own)						0.0214***		
						(0.0025)		
ST (clusters cor. dist)							0.0201***	
							(0.0035)	
WST O*NET weights								0.0205***
								(0.0028)
Fixed-effects								
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	237,038	237,038	237,038	234,504	233,471	237,038	189,743	234,923
R^2	0.03806	0.03787	0.03788	0.03832	0.03763	0.03806	0.03953	0.03770
Within R^2	0.00143	0.00123	0.00124	0.00168	0.00080	0.00143	0.00083	0.00094
Mean dep. var.	0.2656	0.2656	0.2656	0.2655	0.2662	0.2656	0.2703	0.2657

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted sub-market tightness is uses 3 month rolling average of vacancies and unemployment, and transition based weights.
WST (quarter) is weighted sub-market tightness in the unemployment start quarter, using transition based weigths.
WST (month) is weighted sub-market tightness in the unemployment start month, using transition based weigths.
WST (5 month roling average) uses a 5 month rolling average of vacancies and unemployment and transition based weights.
ST (3 month origin occupation only) uses tightness in the origin occupation only and uses 3 mo. rolling average.
WST (3 month weighted, excl. own) uses the weighted sub-market tightness in related occupations, but excludes the origin occupation.
ST (clusters cor. dist) is the unweighted tightness in O*NET defined clusters of related occupations.
WST is the weighted sub-market tightness based on the O*NET weighting scheme.
All tightness measures are standardised w.r.t. the sample standard deviation.

Dependent Variable:	Weighted Sub-Market Tightness			
Model:	(1)	(2)	(3)	(4)
Variables				
Mass Layoffs to Population weighted (mean dev.)	-115,801.0***			
	(14,787.7)			
Log Pre Earnings	0.0434***	0.0248**	0.0476***	0.0226*
	(0.0102)	(0.0103)	(0.0109)	(0.0121)
Mass layoffs to population not cond. on UE (mean dev.)		-7,094.4***		
		(933.0)		
Mass layoffs to population own occupation only (mean dev.)			-58,749.6***	
			(8,587.0)	
Mass layoffs to population related occupations (mean dev.)				-333,963.9***
				(17,341.9)
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Fit statistics				
Observations	163,832	163,832	163,832	163,832
R^2	0.62093	0.59198	0.59851	0.65810
Within R^2	0.14716	0.08203	0.09672	0.23078
F-test (1st stage)	28,200.7	14,582.9	17,482.1	49,069.8

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A9: First stage with alternative instruments

Dependent Variable:	Log Post Earnings - Log Pre Earnings			
Model:	(1)	(2)	(3)	(4)
Instrument:	MLP weighted (mean dev.)	MLP not cond. on UE (mean dev.)	MLP origin occupation only (mean dev.)	MLP related occupations only (mean dev.)
Variables				
Weighted Sub-Market Tightness	0.0212***	0.0300***	0.0183**	0.0228***
	(0.0054)	(0.0042)	(0.0077)	(0.0029)
Log Pre Earnings	-0.5214***	-0.5218***	-0.5213***	-0.5215***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Fit statistics				
Observations	163,832	163,832	163,832	163,832
R^2	0.26427	0.26320	0.26443	0.26414
Within R^2	0.23097	0.22986	0.23114	0.23084
F-test (1st stage), Weighted Sub-Market Tightness	28,200.7	14,582.9	17,482.1	49,069.8

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A10: 2SLS estimation results with alternative instruments

Dependent Variable:	Weighted Sub-Market Tightness			
Model:	(1)	(2)	(3)	(4)
Variables				
Mass Layoffs to Population weighted (mean dev.)	-115,865.5***			
	(15,372.2)			
Mass layoffs to population not cond. on UE (mean dev.)		-7,127.2***		
		(960.4)		
Mass layoffs to population own occupation only (mean dev.)			-58,224.7***	
			(8,788.0)	
Mass layoffs to population related occupations (mean dev.)				-342,419.9***
				(17,136.6)
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Fit statistics				
Observations	237,038	237,038	237,038	237,038
R^2	0.60476	0.57677	0.58096	0.64709
Within R^2	0.14530	0.08478	0.09384	0.23683
F-test (1st stage)	40,284.2	21,951.4	24,540.5	73,536.6

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A11: First stage with alternative instruments (for job finding)

Dependent Variable:	Finds a Job Within 3 Months (indicator)			
Model:	(1)	(2)	(3)	(4)
Instrument:	MLP weighted (mean dev.)	MLP not cond. on UE (mean dev.)	MLP origin occupation only (mean dev.)	MLP related occupations only (mean dev.)
Variables				
Weighted Sub-Market Tightness	0.0460***	0.0501***	0.0470***	0.0435***
	(0.0054)	(0.0063)	(0.0068)	(0.0058)
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Fit statistics				
Observations	237,038	237,038	237,038	237,038
R^2	0.03692	0.03645	0.03681	0.03716
Within R^2	0.00025	-0.00024	0.00014	0.00050
F-test (1st stage), Weighted Sub-Market Tightness	40,284.2	21,951.4	24,540.5	73,536.6

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A12: 2SLS estimation results with alternative instruments (for job finding)

Table A13: Immediate earnings difference and weighted tightness using UE start quarter fixed effects.

Dependent Variables:	Log Post Earnings - Log Pre Earnings		Weighted Sub-Market Tightness	Log Post Earnings - Log Pre Earnings
IV stages			First	Second
Model:	(1)	(2)	(3)	(4)
Variables				
Weighted Sub-Market Tightness	0.0180***	0.0202***		0.0346***
	(0.0036)	(0.0046)		(0.0083)
Log Pre Earnings	-0.4623***	-0.4864***	0.2641***	-0.4675***
	(0.0128)	(0.0161)	(0.0508)	(0.0128)
Mass layoffs to population			-83,318.8***	
			(15,132.5)	
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Unemployment Start Quarter	Yes	Yes	Yes	Yes
Pre-UE Industry (4)	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Fit statistics				
Observations	163,832	14,907	163,832	163,832
F-test (1st stage)			12,665.4	
F-test (1st stage), Weighted Sub-Market Tightness				12,665.4
Wald (1st stage), p-value			3.68×10^{-8}	
Wald (1st stage), p-value, Weighted Sub-Market Tightness				3.68×10^{-8}
Mean dep. var.	-0.1546	-0.1819	1.677	-0.1546

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A14: Job finding in 3 months and weighted tightness using UE start quarter fixed effects.

Dependent Variables:	Finds a Job Within 3 Months (indicator)		Weighted Sub-Market Tightness	Finds a Job Within 3 Months (indicator)
IV stages			First	Second
Model:	(1)	(2)	(3)	(4)
Variables				
Weighted Sub-Market Tightness	0.0178***	0.0088		0.0382***
	(0.0050)	(0.0071)		(0.0128)
Mass layoffs to population			-82,036.2***	
			(15,225.3)	
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Unemployment Start Quarter	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Pre-UE Industry (4)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	237,038	21,630	237,038	237,038
F-test (1st stage)			18,031.5	
F-test (1st stage), Weighted Sub-Market Tightness				18,031.5
Wald (1st stage), p-value			7.13×10^{-8}	
Wald (1st stage), p-value, Weighted Sub-Market Tightness				7.13×10^{-8}
Mean dep. var.	0.2656	0.2651	1.679	0.2656

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	Log Post Earnings - Log Pre Earnings			Finds a Job Within 3 Months (indicator)		
	Entire Sample	50 or younger	Above 50	Entire Sample	50 or younger	Above 50
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Weighted Sub-Market Tightness	0.0149***	0.0121***	0.0217***	0.0241***	0.0194***	0.0359***
	(0.0016)	(0.0017)	(0.0024)	(0.0028)	(0.0029)	(0.0039)
Log Pre Earnings	-0.5211***	-0.5196***	-0.5269***			
	(0.0121)	(0.0127)	(0.0124)			
Fixed-effects						
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	163,832	116,595	47,237	237,038	164,236	72,802
Mean dep. var.	-0.1546	-0.1403	-0.1897	0.2656	0.2843	0.2235

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A15: Main results – split by age

Dependent Variables:	Log Post Earnings - Log Pre Earnings			Finds a Job Within 3 Months (indicator)		
	Entire Sample	Non university educ.	Univeristy educ.	Entire Sample	Non university educ.	Univeristy educ.
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Weighted Sub-Market Tightness	0.0149***	0.0164***	0.0125***	0.0241***	0.0266***	0.0194***
	(0.0016)	(0.0018)	(0.0025)	(0.0028)	(0.0031)	(0.0055)
Log Pre Earnings	-0.5211***	-0.5524***	-0.4786***			
	(0.0121)	(0.0134)	(0.0201)			
Fixed-effects						
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	163,832	117,514	46,318	237,038	170,347	66,691
Mean dep. var.	-0.1546	-0.1519	-0.1612	0.2656	0.2652	0.2667

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A16: Main results – split by univesity education

Table A17: First stage: Panel B Table 5

Dependent Variables:	Log tightness (Origin Occupation Only)	Log tightness in related occupations only	Log tightness (Origin Occupation Only)	Log tightness in related occupations only	Log tightness (Origin Occupation Only)	Log tightness in related occupations only
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Mass layoffs to pop. (origin occupation, de-meaned)	-46,070.9***	-22,321.4***	-41,388.5***	-18,585.7***	-35,723.1***	-12,268.0***
	(5,466.3)	(4,344.9)	(6,694.5)	(3,595.8)	(4,342.5)	(3,266.8)
Mass layoffs to pop. (related occupations only, de-meaned)	-226,124.0***	-259,823.0***	-235,423.9***	-262,437.4***	-44,559.8**	-84,703.6***
	(21,474.9)	(16,943.3)	(21,134.4)	(17,770.7)	(19,805.7)	(10,763.2)
Fixed-effects						
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)			Yes	Yes		
Unemployment Start Quarter					Yes	Yes
Fit statistics						
Observations	161,440	161,440	161,440	161,440	161,440	161,440
F-test (1st stage)	13,021.3	30,084.4	30,205.2	50,065.5	2,600.5	3,388.4

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	Switcher to a non-related occupation (4-digit)					
Displaced		Full sample			Displaced sample	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Log tightness (Origin Occupation Only)	-0.0328***	0.0111***	-0.0341***	-0.0136	0.0138	-0.0150
	(0.0109)	(0.0039)	(0.0109)	(0.0126)	(0.0109)	(0.0120)
Log tightness in related occupations only	0.0778***	0.0365***	0.0758***	0.0748***	0.0488**	0.0709***
	(0.0228)	(0.0087)	(0.0250)	(0.0215)	(0.0208)	(0.0226)
Log tightness in unrelated occupations only	0.0632***	0.0380***	0.0718***	0.0446	0.0190	0.0396
	(0.0225)	(0.0102)	(0.0222)	(0.0274)	(0.0222)	(0.0411)
Fixed-effects						
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)		Yes			Yes	
Unemployment Start Quarter			Yes			Yes
Fit statistics						
Observations	161,440	161,440	161,440	14,544	14,544	14,544
Mean dep. var.	0.3446	0.3446	0.3446	0.3634	0.3634	0.3634

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A18: Tightness in related and unrelated occupations and occupational switching

Dependent Variables:	Downwards Switchers (PC1 definition, excl. rel.)				Downwards Switcher (cluster wage rank)				O*NET Distance			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Weighted Sub-Market Tightness	-0.0109***				-0.0087***				-0.0013			
	(0.0034)				(0.0033)				(0.0042)			
Log tightness (3 month origin occupation only)		-0.0167***	-0.0105*	-0.0098*		-0.0124***	0.0002	0.0038		-0.0012	0.0071	0.0106
		(0.0040)	(0.0057)	(0.0055)		(0.0037)	(0.0056)	(0.0054)		(0.0056)	(0.0079)	(0.0081)
Log tightness in related occupations only			-0.0110*	-0.0080			-0.0221***	-0.0058			-0.0148*	0.0007
			(0.0059)	(0.0085)			(0.0070)	(0.0081)			(0.0089)	(0.0103)
Log tightness in unrelated occupations only				-0.0071				-0.0384***				-0.0365**
				(0.0117)				(0.0103)				(0.0149)
Fixed-effects												
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commute area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	72,076	70,717	70,717	70,717	72,076	70,717	70,717	70,717	72,076	70,717	70,717	70,717
Mean dep. var.	0.4139	0.4134	0.4134	0.4134	0.5012	0.4992	0.4992	0.4992	1.796	1.793	1.793	1.793

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted tightness is standardised by the sample standard deviation (0.3).
The dependent variables are presented in subsection 3.1
Downwards Switchers (PC1 definition, excl. rel.) is an indicator of switching downwards measured by the first principal component of the O*NET data.
It excludes transitions to the top ten related occupations by the O*NET measure.
Downwards Switcher (cluster wage rank) is an indicator of moving downwards in the wage rank of clusters of O*NET related occupations.
O*NET distance is standardised w.r.t the sample standard deviation.

Table A19: Downwards transitions and tightness

Dependent Variables:	Downwards Switchers (PC1 definition, excl. rel.)	Downwards Switcher (cluster wage rank)	O*NET Distance	Weighted Sub-Market Tightness
Model:	(1)	(2)	(3)	(4)
Variables				
Weighted Sub-Market Tightness	-0.0164*	-0.0176**	0.0073	
	(0.0085)	(0.0080)	(0.0086)	
Mass Layoffs to Population weighted (mean dev.)				-118,527.0***
				(16,766.9)
Fixed-effects				
Level of Education	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes
Fit statistics				
Observations	72,076	72,076	72,076	72,076
F-test (1st stage), Weighted Sub-Market Tightness	10,950.2	10,950.2	10,950.2	
Mean dep. var.	0.4139	0.5012	1.796	1.693

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A20: 2SLS Downwards switching and tightness

Dependent Variables:	Log Post Earnings - Log Pre Earnings	Finds a Job Within 3 Months (indicator)
Model:	(1)	(2)
Variables		
Mismatched	-0.0292***	-0.0426***
	(0.0025)	(0.0054)
Log Pre Earnings	-0.5241***	
	(0.0122)	
Fixed-effects		
Level of Education	Yes	Yes
Age (dummy for each value)	Yes	Yes
Commuting Area	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes
Female	Yes	Yes
Fit statistics		
Observations	121,886	176,021
R^2	0.26511	0.03993
Within R^2	0.23199	0.00136
Mean dep. var.	-0.1548	0.2698

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Mismatched is an indicator of belonging to the bottom quartile of submarkets in terms of weighted tightness in the period 2011-2020.
The comparison group are workers that belong to the upper two quartiles of submarket in terms of weighted tightness in the period.

Table A21: Binary mismatch treatment and main outcomes

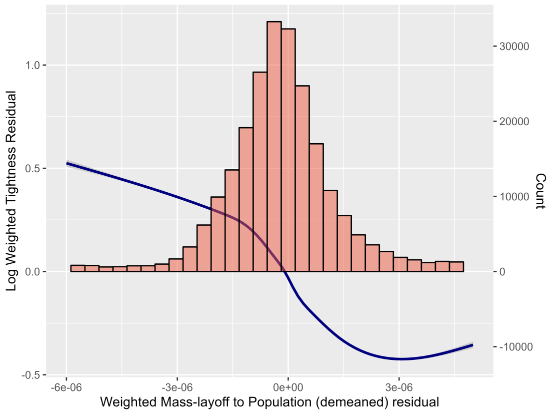


Figure B1: Residualised log of weighted tightness and residualised instrument
The horizontal axis shows weighted mass layoffs to population, where occupation means have been subtracted, on the horizontal axis and weighted sub-market tightness on the vertical axis (left axis). Both are residulised according to column 3 of Table 1. The line shows a smooth conditional mean of weighted tightness residuals conditional on weighted mass layoffs to population residuals. The histogram shows the number of observations in the bins (right axis).

B Results with a log specification

Dependent Variable:	Log Weighted Tightness					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	0.3976***			-2.744***		
	(0.0340)			(0.4260)		
Mass Layoffs to Population weighted (mean dev.)	-94,888.8***	-88,911.6***	-85,942.1***	-97,238.2***	-91,300.5***	-88,019.5***
	(14,044.4)	(13,378.8)	(13,045.2)	(14,368.3)	(13,447.4)	(13,032.3)
Log Pre Earnings				0.3079***	0.2013***	0.0321***
				(0.0412)	(0.0305)	(0.0074)
Fixed-effects						
Level of Education		Yes	Yes		Yes	Yes
Age (dummy for each value)		Yes	Yes		Yes	Yes
Female		Yes	Yes		Yes	Yes
Commuting Area		Yes	Yes		Yes	Yes
Pre-Unemployment Occupation (4 digit)			Yes			Yes
Fit statistics						
Observations	237,038	237,038	237,038	163,832	163,832	163,832
R^2	0.13536	0.27719	0.54380	0.16987	0.30099	0.55601
Within R^2		0.14018	0.19010		0.15717	0.19623
F-test (1st stage)	37,109.2	38,631.9	55,617.9	27,059.2	28,066.9	39,904.1
Wald (1st stage), p-value	1.42×10^{-11}	3.02×10^{-11}	4.47×10^{-11}	1.31×10^{-11}	1.13×10^{-11}	1.44×10^{-11}

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B1: First stage: Log weighted tightness.

Table B2: Job finding in three months and log weighted tightness

Dependent Variable:	Finds a Job Within 3 Months (indicator)					
	OLS				2SLS	
	Entire Sample		Displaced		Entire Sample	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Log Weighted Tightness	0.0345***	0.0425***	0.0224**	0.0473***	0.0605***	0.0620***
	(0.0081)	(0.0044)	(0.0103)	(0.0098)	(0.0090)	(0.0073)
Fixed-effects						
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)		Yes		Yes		Yes
Fit statistics						
Observations	237,038	237,038	21,630	21,630	237,038	237,038
F-test (1st stage), Log Weighted Tightness					38,631.9	55,617.9
Wald (1st stage), p-value, Log Weighted Tightness					3.02×10^{-11}	4.47×10^{-11}
Mean dep. var.	0.2656	0.2656	0.2651	0.2651	0.2656	0.2656

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
The instrument is mass layoffs to population (occupation mean dev.)
The corresponding first stage is reported in Table B1

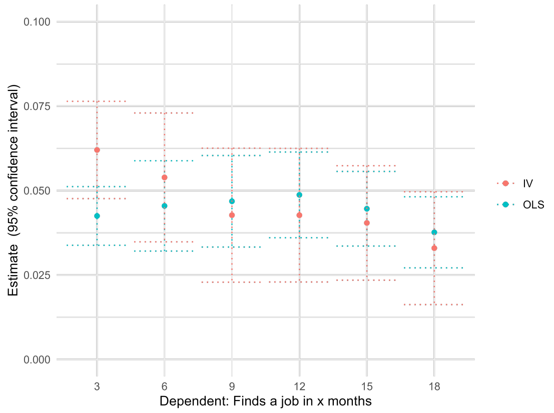


Figure B2: Jog finding and log tightness

The upper panel reports estimation results of a similar regression as in col. 3 and col.6 of Table 2. The dependent variable is an indicator of finding a job in 3, 6, 9, 12, 15, and 18 months. The lower panel shows the mean of the dependent vairable.

Dependent Variable:	Log Post Earnings - Log Pre Earnings								
	OLS						2SLS		
	Entire Sample			Displaced			Entire Sample		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Constant	3.360***			3.640***			3.352***		
	(0.1397)			(0.1806)			(0.1433)		
Log Weighted Tightness	0.0288***	0.0282***	0.0269***	0.0295***	0.0272***	0.0302***	0.0260***	0.0268***	0.0279***
	(0.0060)	(0.0037)	(0.0023)	(0.0077)	(0.0057)	(0.0053)	(0.0085)	(0.0074)	(0.0077)
Log Pre Earnings	-0.3458***	-0.4286***	-0.5213***	-0.3747***	-0.4584***	-0.5353***	-0.3449***	-0.4283***	-0.5214***
	(0.0135)	(0.0123)	(0.0121)	(0.0175)	(0.0163)	(0.0154)	(0.0140)	(0.0126)	(0.0122)
Fixed-effects									
Level of Education		Yes	Yes		Yes	Yes		Yes	Yes
Age (dummy for each value)		Yes	Yes		Yes	Yes		Yes	Yes
Female		Yes	Yes		Yes	Yes		Yes	Yes
Commuting Area		Yes	Yes		Yes	Yes		Yes	Yes
Pre-Unemployment Occupation (4 digit)			Yes			Yes			Yes
Fit statistics									
Observations	163,832	163,832	163,832	14,907	14,907	14,907	163,832	163,832	163,832
R^2	0.16667	0.21847	0.26501	0.19927	0.25937	0.32220	0.16663	0.21846	0.26500
Within R^2		0.20527	0.23175		0.24256	0.25848		0.20526	0.23174
F-test (1st stage), Log Weighted Tightness							27,059.2	28,066.9	39,904.1
Wald (1st stage), p-value, Log Weighted Tightness							1.31×10^{-11}	1.13×10^{-11}	1.44×10^{-11}
Mean dep. var.	-0.1546	-0.1546	-0.1546	-0.1819	-0.1819	-0.1819	-0.1546	-0.1546	-0.1546

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
The instrument is mass layoffs to population (occupation mean dev.)
The corresponding first stage is reported in Table B1

Table B3: Log weighted tightness and immediate earnings difference

Table B4: Log weighted tightness and earnings in 0-3 following UE entry

Dependent Variables:	Yearly earnings year of entering UE (kr.)	Yearly earnings 1st year after entering UE (kr.)	Yearly earnings 2nd year after entering UE (kr.)	Yearly earnings 3rd year after entering UE (kr.)
Model:	(1)	(2)	(3)	(4)
Variables				
Log Weighted Tightness	6,109.4***	17,323.4***	14,548.9***	10,156.0***
	(1,083.5)	(1,720.5)	(1,654.7)	(1,955.7)
Yearly earnings year before UE (kr.)	0.5964***	0.3523***	0.4053***	0.4057***
	(0.0184)	(0.0144)	(0.0146)	(0.0133)
Fixed-effects				
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes
Level of Education	Yes	Yes	Yes	Yes
female	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes
Fit statistics				
Observations	204,641	204,641	204,641	181,155
R^2	0.52187	0.22160	0.26786	0.26121
Within R^2	0.30905	0.08492	0.10064	0.09181
Mean dep. var.	257,079.7	186,111.0	232,448.1	243,449.7

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	Log Post Earnings - Log Pre Earnings							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Log Weighted Tightness	0.0269***							
	(0.0023)							
Log Pre Earnings	-0.5213***	-0.5214***	-0.5212***	-0.5221***	-0.5217***	-0.5211***	-0.5241***	-0.5222***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0146)	(0.0122)
Log WST (quarter)		0.0240***						
		(0.0022)						
Log WST (month)			0.0260***					
			(0.0021)					
Log WST (5 month rolling average)				0.0270***				
				(0.0023)				
Log ST (3 month own occupation only)					0.0186***			
					(0.0020)			
Log WST (3 month weighted, excl. own)						0.0229***		
						(0.0022)		
Log ST (clusters cor. dist)							0.0152***	
							(0.0028)	
Log WST O*NET weights								0.0253***
								(0.0023)
Fixed-effects								
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	163,832	163,832	163,832	161,838	161,440	163,832	131,742	162,803
R^2	0.26501	0.26478	0.26496	0.26585	0.26458	0.26457	0.26345	0.26521
Within R^2	0.23175	0.23151	0.23169	0.23244	0.23159	0.23129	0.23102	0.23187
Mean dep. var.	-0.1546	-0.1546	-0.1546	-0.1552	-0.1542	-0.1546	-0.1524	-0.1546

Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted sub-market tightness is uses 3 month rolling average of vacancies and unemployment, and transition based weights.
WST (quarter) is weighted sub-market tightness in the unemployment start quarter, using transition based weigths.
WST (month) is weighted sub-market tightness in the unemployment start month, using transition based weigths.
WST (5 month roling average) uses a 5 month rolling average of vacancies and unemployment and transition based weights.
ST (3 month origin occupation only) uses tightness in the origin occupation only and uses 3 mo. rolling average.
WST (3 month weighted, excl. own) uses the weighted sub-market tightness in related occupations, but excludes the origin occupation.
ST (clusters cor. dist) is the unweighted tightness in O*NET defined clusters of related occupations.
WST is the weighted sub-market tightness based on the O*NET weighting scheme.

Table B5: Immediate earnings difference and log alternative tightness measures.

Dependent Variable:	Finds a Job Within 3 Months (indicator)							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Log Weighted Tightness	0.0425***							
	(0.0044)							
Log WST (quarter)		0.0413***						
		(0.0037)						
Log WST (month)			0.0396***					
			(0.0041)					
Log WST (5 month rolling average)				0.0457***				
				(0.0046)				
Log ST (3 month own occupation only)					0.0262***			
					(0.0035)			
Log WST (3 month weighted, excl. own)						0.0382***		
						(0.0046)		
Log ST (clusters cor. dist)							0.0244***	
							(0.0044)	
Log WST O*NET weights								0.0331***
								(0.0042)
Fixed-effects								
Level of Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (dummy for each value)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Unemployment Occupation (4 digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	237,038	237,038	237,038	234,504	233,471	237,038	189,743	234,923
R^2	0.03848	0.03855	0.03831	0.03873	0.03801	0.03819	0.03981	0.03800
Within R^2	0.00187	0.00193	0.00169	0.00211	0.00120	0.00157	0.00113	0.00125
Mean dep. var.	0.2656	0.2656	0.2656	0.2655	0.2662	0.2656	0.2703	0.2657

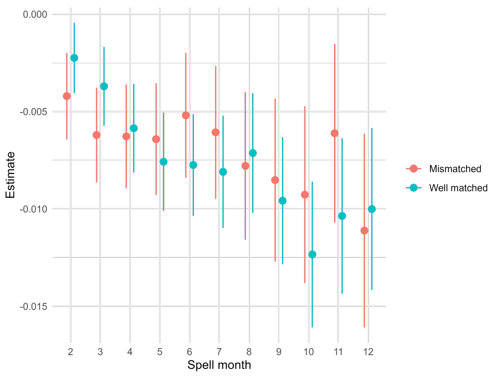
Clustered (Pre-Unemployment Occupation (4 digit)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Weighted sub-market tightness is uses 3 month rolling average of vacancies and unemployment, and transition based weights.
WST (quarter) is weighted sub-market tightness in the unemployment start quarter, using transition based weigths.
WST (month) is weighted sub-market tightness in the unemployment start month, using transition based weigths.
WST (5 month roling average) uses a 5 month rolling average of vacancies and unemployment and transition based weights.
ST (3 month origin occupation only) uses tightness in the origin occupation only and uses 3 mo. rolling average.
WST (3 month weighted, excl. own) uses the weighted sub-market tightness in related occupations, but excludes the origin occupation.
ST (clusters cor. dist) is the unweighted tightness in O*NET defined clusters of related occupations.
WST is the weighted sub-market tightness based on the O*NET weighting scheme.

Table B6: Job finding in 3 months and log alternative tightness measures.

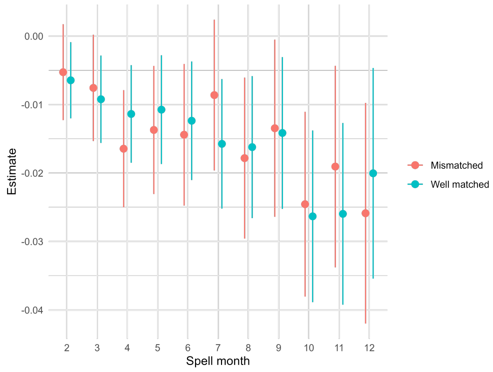
C Additional Applications results

Figure C1: Change in applications over the UE spell by mismatch

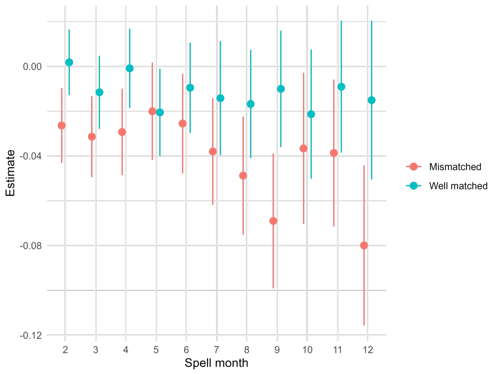
The left panel shows estimates of regression equation (3). The figure shows estimates on spell month dummies for mismatched workers (red line) and non-mismatched workers (blue line). 95% confidence intervals are shown, standard errors are clustered at the individual level. The right panel shows the estimates shifted up by the first month mean.



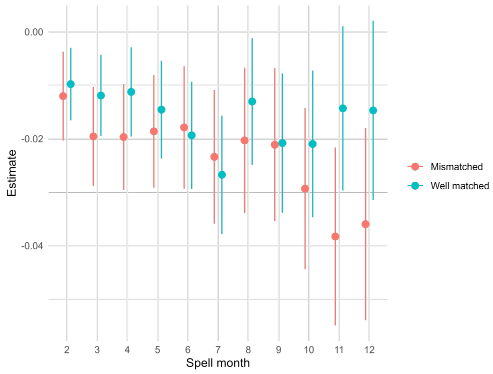
(a) Applied for wages.



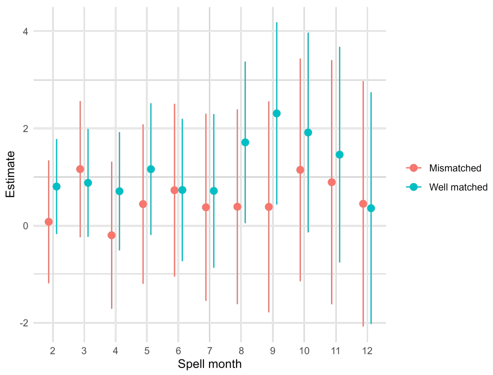
(b) Share of applications in a related occupation.



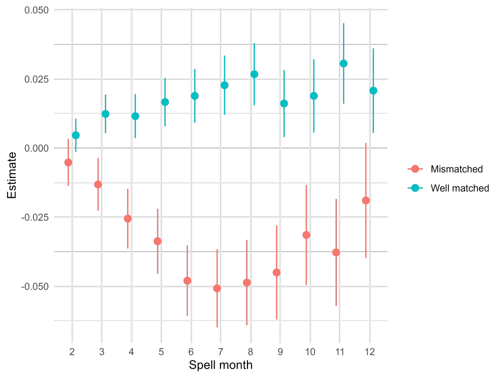
(c) Applied for firm.



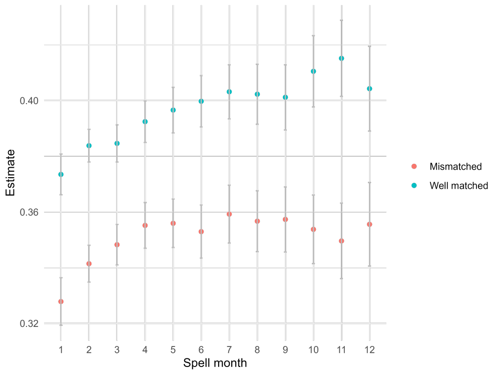
(d) Share of application to a related industry



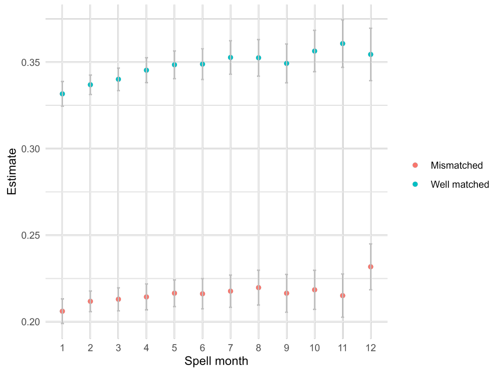
(e) Applied for commuting time.



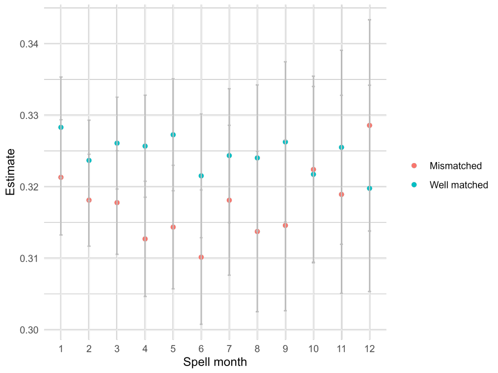
(f) Share of application to a tighter submarket.



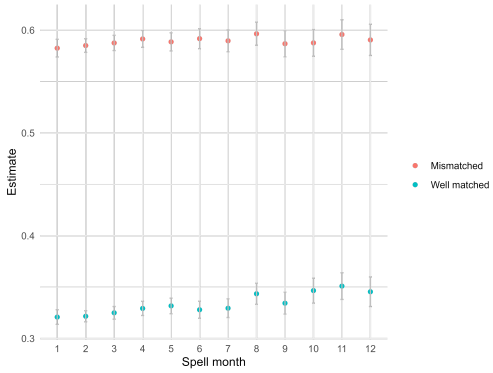
(a) Share of downwards applications (cluster wage rank)



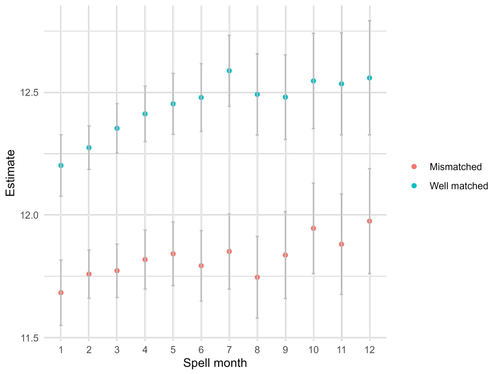
(b) Share of downwards applications PC1



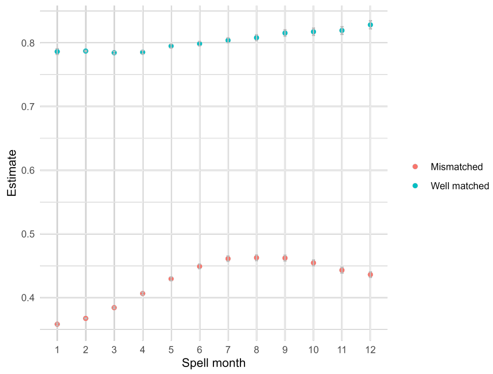
(c) Share of downwards applications PC2



(d) Share of downwards applications PC3



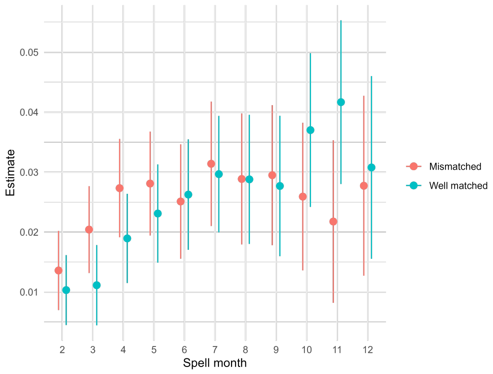
(e) Average distance applied for.



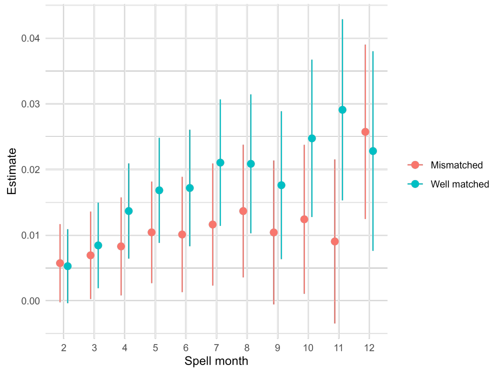
(f) Origin occupation tightness

Figure C2: Applications over time in UE

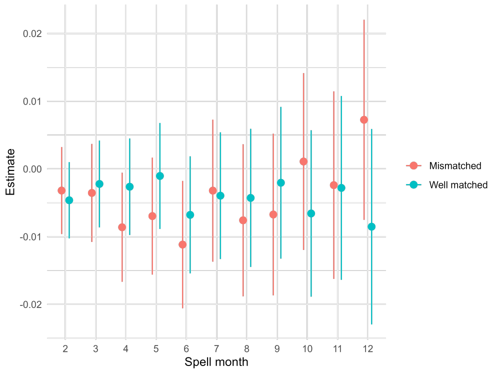
The figure shows estimates on spell month dummies for mismatched workers (blue line) and non-mismatched workers (red line). 95% confidence intervals are reported, standard errors are clustered at the individual level. The dependent variables are described in section 3.1



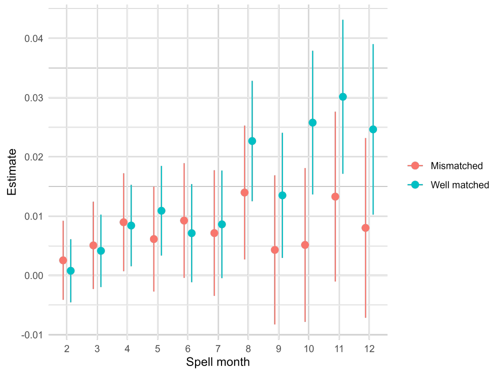
(a) Share of downwards applications (cluster wage rank)



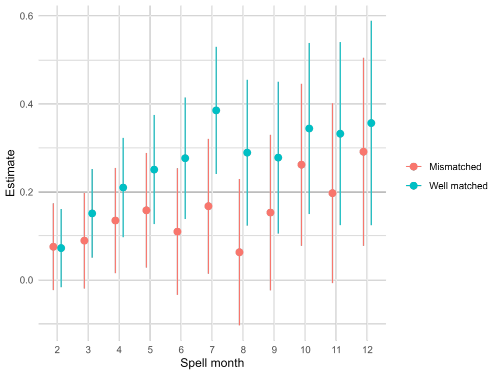
(b) Share of downwards applications PC1



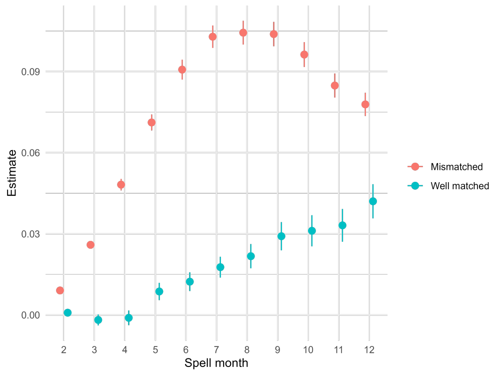
(c) Share of downwards applications PC2



(d) Share of downwards applications PC3



(e) Average distance applied for.



(f) Origin occupation tightness

Figure C3: Changes applications over time in UE

The figure shows estimates on spell month dummies for mismatched workers (blue line) and non-mismatched workers (red line). 95% confidence intervals are reported, standard errors are clustered at the individual level. The dependent variables are described in section 3.1

D Other Supplementary Materials

D.1 The DISCO Occupational Classification System

DISCO is a six-digit variable. The first digit groups into 10 main categories:

0. Military and National Guard
1. Top Management
2. Work that Requires Knowledge at the Highest Level
3. Work that Requires Knowledge at the Intermediate Level
4. Office Work
5. Work in Service and Sales
6. Work in Agriculture, Forestry and Fishing
7. Crafts
8. Process and Machine Operator Work, Transport and Construction Work
9. Other Manual Work

An example of the transition at the first digit level would be from office work (4) to work in service and sales (5). The first two digits of the DISCO further classify into 42 groups. An example of a transition at the second digit level is a transition from Work in Sales (52) to Care-giving Work (53). The first 3 digits classify into 125 groups. An example of a transition at the third digit level is a transition from Work in arts and creative subjects (265) to Legal work (261). The first four DISCO digits classify into 429 groups. An example of a transition is from Work in Economics (2631) to Work in Psychology (2634).The six digits further classify into 563 groups.

D.2 O*NET Disco Mapping

To map the O*NET data to the Danish DISCO occupational classification, the following procedure is followed. First, the O*NET-SOC18 codes are mapped to SOC 2018 by the crosswalk provided by O*NET. Second, SOC 2018 codes are mapped to SOC10 using the crosswalk from the US Bureau of Labour Statistics (BLS). Third, SOC10 occupation codes are mapped to ISCO08 codes using the crosswalk from the US BLS. Finally, the ISCO08 codes are mapped to the DISCO08 codes. This links each DISCO08 code to one or more O*NET-SOC18 codes. For each DISCO08 that more than one O*NET-SOC18 are linked to, we take the mean of the O*NET attributes to represent the four-digit DISCO08 occupation. 418 of 429 DISCO (4 digit) occupations are successfully mapped to O*NET attributes.