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Matching Efficiency and The Composition of the Unemployed

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Abstract

This paper studies how compositional changes among the unemployed and the matching efficiency in the labor market affects the matching process between establishments and job seekers in Norway. We use an aggregate matching function which takes into account dispersion across local labor markets, and allow for variation in search intensity among the unemployed. Using detailed micro-data on individuals and establishments for the period 2001–2024, we find that the decreasing matching efficiency in the labor market over the period 2007–2019 was driven by a increased dispersion of matching rates across local labor markets due to differential labor market conditions, and not a change in the allocation of unemployed across different local labor markets with inherently different matching efficiencies.

Keywords: Matching Efficiency; Composition Effects; Vacancies

JEL Classification: J23

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Sammendrag

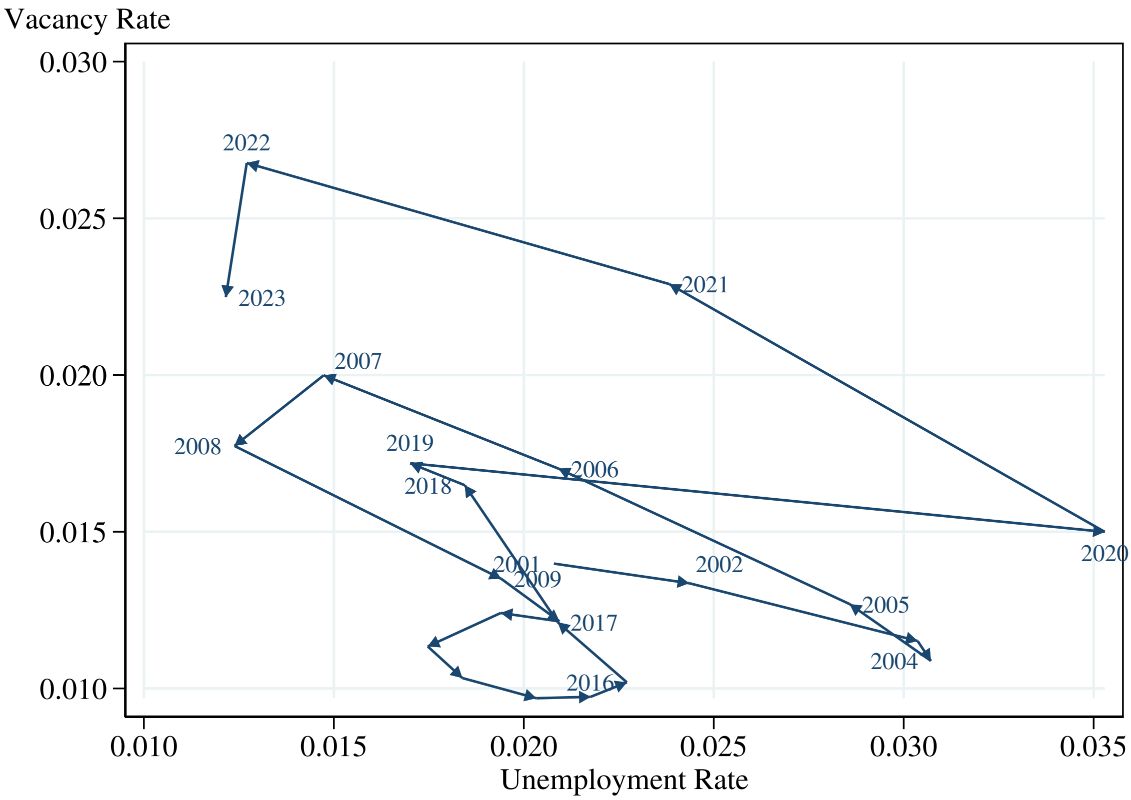
I denne artikkelen undersøker vi hvordan endringer i sammensetningen av arbeidsledige og matching-effektiviteten i arbeidsmarkedet påvirker matching-prosessen mellom bedrifter og arbeidsledige i Norge. Vi bruker en aggregert matching-funksjon som tar hensyn til variasjoner på tvers av lokale arbeidsmarkeder, samt variasjon i søkeintensitet blant de arbeidsledige. Ved å bruke detaljerte mikrodata om individer og bedrifter for perioden 2001–2024, finner vi at den fallende matching-effektiviteten i arbeidsmarkedet i perioden 2007–2019 ble drevet av større variasjon i matching-rater på tvers av lokale arbeidsmarkeder på grunn av ulike arbeidsmarkedsforhold, og ikke en endring i sammensetningen av arbeidsledige på tvers av lokale arbeidsmarkeder med forskjellig matching-effektivitet.

1 Introduction

The matching rate in the labor market, which expresses the rate at which workers are matched with vacant jobs, is an important indicator of the functioning of the labor market. This rate varies over the business cycle, and its evolution is affected by the availability of vacant jobs and the matching efficiency of the labor market. The aim of this paper is to decompose the evolution of the matching efficiency of the labor market into the effect of the changing composition of job seekers in the labor market (which yields variation in the average search effort) and the effect of dispersion of labor market conditions across local labor markets.

The canonical matching function $m = f(V, U, A)$, which maps the number of job seekers (U) and the number of vacant jobs (V) into new matches (m) in the labor market, serves as a modeling device for understanding frictional labor markets on an aggregate level. The matching function is commonly used to understand the evolution of mismatch in the labor market, and the associated shifts in the Beveridge curve as shown in Figure 1, over time. A is the parameter capturing the matching efficiency between establishments and unemployed individuals, and is the main object of interest in this paper.

Figure 1: Beveridge Curve.



Note: Average stock of unemployed individuals and posted vacancies per year, divided by the average size of the labor force per year.
Source: Authors' own calculations using data from Statistics Norway and the Norwegian Labour and Welfare Administration (NAV).

In the literature, the matching function is often specified as a Cobb-Douglas matching function. We augment the Cobb-Douglas matching function to take into account several sub-markets within the aggregate labor market, and use this to characterize movements in the matching efficiency that can be ascribed to compositional effects in the labor market. To do so, we allow the matching efficiency parameter (A) to vary across worker types (based on age, gender, education level and duration of unemployment spell) and local labor markets (based on occupation and geographical location). To estimate the evolution of the matching efficiency across the business cycle, we use detailed Norwegian register data for both workers and establishments, spanning the years 2001 to 2024.

Having estimated the matching function, we decompose the evolution of the matching efficiency into three distinct components. The first component is a composition effect concerning the change in characteristics of the unemployed, while the second component is a composition effect concerning the change in the distribution of unemployment across different local labor markets. The third and last component concerns the effect of dispersion across local labor markets on the aggregate matching efficiency. From this decomposition exercise, we find that the decreasing matching efficiency in the labor market over the period 2007–2019 was driven by a increased dispersion of of matching rates across local labor markets due to differential labor market conditions, and not a change in the allocation of unemployed across different local labor markets with inherently different matching efficiencies.

2 Related Literature

Petrongolo and Pissarides (2001) presented an early survey of the theory behind the matching function, and the empirical findings from estimating this function. While there are several ways to specify the matching function (see e.g. Lange and Papageorgiou (2020) for a non-parametric approach), studies published after this survey have commonly used the Cobb-Douglas matching function to study labor market movements. Several issues regarding the matching function, such as simultaneity problems (Borowczyk-Martins et al., 2013), functional misspecification (Bernstein et al., 2022) and lacking measures of the number of job seekers (Hall and Schulhofer-Wohl, 2018), have been studied.

Barnichon and Figura (2015) estimate an aggregate matching function that takes into account worker heterogeneity and labor market segmentation using data from the United States. They find that the derived matching efficiency declines when the characteristics of the unemployed deteriorate ("composition effect") or when the dispersion in local labor market conditions increases ("dispersion effect"). Pizzinelli and Speigner (2017) use the same approach for studying the how compositional changes in the labor market in the United Kingdom affects the matching process, and find that compositional changes improved aggregate search intensity (by means of increased transition rates from unemployment to employment) prior to the financial crisis in 2008. In this period, the aggregate matching efficiency fell but the fall was masked by the increased search intensity due to the compositional changes in the labor market.

Şahin et al. (2014) compare the observed number of hires with an optimal number of hires in local labor markets, with the optimal hires being the the number of hires based on a social planner allocation of hires across local labor markets. Based on this, the authors construct a mismatch index for the United States labor market, where the difference between the observed unemployment rate and the counterfactual unemployment rate constitutes "mismatch unemployment". The matching function used for constructing the mismatch index has a Cobb-Douglas functional form, with both sector-specific matching efficiencies and a common aggregate component. The definition of local labor markets is based on three separate dimensions, namely industry, occupation and geographic classification.

While the number of vacancies is an imperfect measures of the number of vacant jobs, especially given the presence of informal job matching and phantom vacancies, there are several studies highlighting that there is a positive vacancy yield, i.e. that the posting of vacancies is associated with hires on the establishment-level (Davis et al., 2013). In the Norwegian context, Audoly et al. (2024) find that 87.7 percent of all publicly posted non-staffing agency vacancies from the Norwegian Labour and Welfare Administration (NAV) lead to a hire within the following six months. As we use the same vacancy data from NAV, we are therefore able to measure the number of vacant jobs, albeit not in a perfect manner.

3 Framework

Assuming a constant elasticity of substitution, the aggregate Cobb-Douglas matching function in discrete time can be written as

$$m_t = A_t U_t^{\sigma} V_t^{1-\sigma} \tag{1}$$

where m_t is the number of new hires at time t, U_t is the number of job seekers at time t, and V_t is the stock of vacancies at time t. A_t is a parameter capturing the matching efficiency between establishments and unemployed individuals at time t, conditional on the number of vacancies and the number of unemployed. Using Equation (1), the matching rate of unemployed job seekers at time t ($f_t \equiv m_t/U_t$) is a function of a measure of labor market tightness at time t ($\theta_t \equiv V_t/U_t$):

$$f_t = A_t \theta_t^{1-\sigma}. \tag{2}$$

However, the aggregate number of matches is derived from several distinct local labor markets consisting of different worker types. Following Barnichon and Figura (2015) and Lisauskaite (2022) and assuming no across-market mobility, the number of new hires at time t in a local labor market i is given by

$$m_{it} = A_i V_{it}^{1-\sigma} (s_{it} U_{it})^{\sigma} \tag{3}$$

where the average search effort in the local labor market i at time t (s_{it}) is defined as an weighted sum of search effort across worker types (j) in local labor market i at time t:

$$s_{it} \equiv \sum_{j=1}^{J} \frac{U_{jit}}{U_{it}} s_{ijt}. \tag{4}$$

The weights (U_{jit}/U_{it}) simply reflect the fraction of job seekers that are of type j in local labor market i at time t. An example of a worker type j could be a *young male* with a *college degree* that has been unemployed for *60 days*. An example of a local labor market i could be posted vacant positions as *accounting advisors* within the *Oslo region* (the capitol region).

Taking into account the existence of these local labor markets and worker types, the aggregate matching function is again given by Equation (1), but now the matching efficiency parameter (A_t) is equal to:

$$A_t = \sum_{i=1}^{I} \frac{U_{it}}{U_t} A_i s_{it}^{\sigma} \left(\frac{\theta_{it}}{\theta_t} \right)^{1-\sigma}. \tag{5}$$

With each worker type j supplying s_{jit} units of search effort in local labor market i at time t, the matching rate of job seekers at time t in local labor market i of type j (f_{jit}) becomes:

$$\begin{aligned} f_{jit} &= \frac{s_{jit} m_{it}}{s_{it} U_{it}} \\ &= A_i \frac{s_{jit}}{s_{it}} s_{it}^{\sigma} \theta_{it}^{1-\sigma}. \end{aligned} \tag{6}$$

By virtue of the Poisson process underlying the arrival rate of job offers, the matching probability of worker type j in local labor market i over time t (F_{jit}) is then:

$$\begin{aligned} F_{jit} &= 1 - \exp\left(-f_{jit}\right) \\ &= 1 - \exp\left(-A_i \frac{s_{jit}}{s_{it}} s_{it}^{\sigma} \theta_{it}^{1-\sigma} \right). \end{aligned} \tag{7}$$

While the search effort of unemployed job seekers is not directly observable, we assign a data-based worker type-specific search effort based on individual-level characteristics (X_{jit}). To bound the search effort between 0 and 1, we use the following parametrization:

$$s_{jit} = \exp\left(X_{jit} \beta\right). \tag{8}$$

With this parametrization, the matching probability over time t for an individual (we suppress the subscript for individuals for notational ease) can be expressed as:

$$\begin{aligned} F_{jit} &= 1-\exp\left(-A_i \frac{s_{jit}}{s_{it}} s_{it}^{\sigma} \theta_{it}^{1-\sigma}\right) \\ &= 1-\exp\left(-A_i \frac{\exp\left(X_{jit}\beta\right)}{\sum\limits_{j=1}^{J} \frac{U_{jit}}{U_{it}} \exp\left(X_{jit}\beta\right)} \left[\sum_{j=1}^{J} \frac{U_{jit}}{U_{it}} \exp\left(X_{jit}\beta\right)\right]^{\sigma} \theta_{it}^{1-\sigma}\right) \\ &= 1-\exp\left(-A_i \exp\left(X_{jit}\beta\right) \left(\sum_{j=1}^{J} \frac{U_{jit}}{U_{it}} \exp\left(X_{jit}\beta\right)\right)^{\sigma-1} \theta_{it}^{1-\sigma}\right). \end{aligned} \tag{9}$$

If there is no worker heterogeneity in terms of search effort (such that $s_{jit} = s_t$) and no dispersion across local labor markets (such that $\theta_{it} = \theta_t$), the matching probability over time t simplifies to:

$$\begin{aligned} F_{jit} &= 1-\exp\left(-A_i \frac{s_{jit}}{s_{it}} s_{it}^{\sigma} \theta_{it}^{1-\sigma}\right) \\ &= 1-\exp\left(-\theta_t^{1-\sigma}\right) \\ &= F_t. \end{aligned} \tag{10}$$

With the matching process following a Bernoulli distribution with a probability mass function equal to $P_{jit} = (1-F_{jit})^{1-y_{jit}} F_{jit}^{y_{jit}}$, where y_{jit} equals 1 if individual of worker type j in local labor market i finds a job over time t and zero otherwise and F_{jit} is defined in Equation (9), this gives us the following log-likelihood function to be estimated:

$$\ell\left(\beta, A_i, \sigma\right) = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} \left[(1-y_{jit}) \log\left(1-F_{jit}\right) + y_{jit} \log\left(F_{jit}\right)\right]. \tag{11}$$

Correspondingly, when there is no worker heterogeneity in terms of search effort and no local labor market dispersion, as in Equation (10), the log-likelihood function in Equation (11) simplifies to:

$$\ell\left(\sigma\right) = \sum_{t=1}^{T} (1-y_t) \log\left(1-F_t\right) + y_{jit} \log\left(F_t\right). \tag{12}$$

4 Data Sources

4.1 Employment

As the basis for the labor market status of individuals, we use data from the linked employer-employee registers. The data is available at an annual frequency in the period 1995 to 2014 (with sampling in November of each year), and at a monthly frequency during the period January 2015 to August 2024, and contains comprehensive information about the population of all wage earners in Norway, both in terms of wage, occupation and industry, as well as demographic background variables. In addition, the data covers all individuals outside the labor force, with recorded demographic background variables.

Based on the start and stop dates of employment in the annual data, we construct a consistent monthly data set for the period 1995–2014. To take into account the data break going from the annual data (up to and including 2014) to the monthly data (from 2015 and onwards), and the potential differential seasonal variation across these data sources, we use indicator variables for each month and allow for a break in the seasonal pattern going from 2014 to 2015. This is because the annual data for the period leading up to 2015 shows considerable bunching of start dates and stop dates at January 1$^{\text{st}}$ and December 31$^{\text{st}}$, respectively.

4.2 Unemployment

To measure unemployment spells, we use the unemployment register from the Norwegian Labour and Welfare Administration (NAV). The register contains monthly information on the receipt of unemployment benefits and other welfare benefits over the period May 2001 to December 2023. The data contains information on all individuals who are either full-time unemployed or part-time unemployed, as well as participants in active labor market programs. The data also contains the occupation of the unemployed individual prior to the unemployment spell, the desired occupation of the unemployed individual and the length of the unemployment spell.

4.3 Vacancies

For measuring the number of posted vacancies, we use establishment-level data from NAV. The data is available at a monthly frequency during the period May 2001 to December 2023, and contains information about the number of job openings in each vacancy posting, the detailed occupational code of job, industry affiliation of the establishment, and the start and stop date of the vacancy posting. This data only contains posted vacancies registered with NAV job centers, by NAV centrally or at NAV's website.[1] In our analysis, the data therefore restricts us to only consider formally posted vacancies, and disregard any vacancies posted through informal channels.

4.4 Sample Selection

Unemployed

For the individual-level data, we restrict the sample to include resident unemployed individuals aged 16–74 with a valid municipality identifier and a recorded past occupational code (both of which are used to map them to a local labor market), and whose unemployment spell is longer than 14 days. In addition, we discard unemployed individuals with a past occupational code from the military service, as individuals have a right to unemployment benefits after being discharged from compulsory military service. We discard unemployed individuals with a past occupation of craft and related trades workers or agriculture, forestry or fishery due to the nature of vacancy posting for the two industries in which most of workers with these occupational groups work, as explained below.

Vacancies

In terms of the vacancy data, we discard vacancies posted by establishments that are staffing and recruitment agencies, as the actual geographical location of the workplace based on the establishment identifier is not known for these vacancies. In addition, and for the same reasons as for the unemployed individuals, we discard vacancies whose occupational code is not recorded, or is associated with the military service, agriculture, forestry, fishery or craft and related trades workers. The reason for dropping vacancies whose occupational code is craft and related trades workers or agriculture, forestry or fishery is that a large fraction of vacant positions within the construction and agriculture, forestry and fishing industries, where most workers with these two occupational groups are employed, is announced via non-posted vacancies (Hagtvedt, 2005). Table 1 on the next page shows the size of the unemployed sample and the vacancies sample when the sample selection criteria are applied, where the final sample consists of 11,194,135 person-month observations of unemployed and 4,813,773 posting-month observations of posted vacancies.

[1] From August 2017 to December 2017, there was a marked increase in the vacancy flow based on the NAV data, due to improved data availability from a large online job posting database (Finn.no).

Table 1: Sample Restrictions, Unemployed and Vacancies

Sample restriction	Observations
Full sample of unemployed (residents aged 16–74)	19,802,553
↪ Valid municipality and past occupational identifier	15,481,071
↪ Unemployment spell longer than 14 days	12,986,146
↪ Not from a past military service occupation	12,906,195
↪ Not from a past crafts and related trades workers occupation	11,361,319
↪ Not from a past agriculture, forestry or fishery occupation	11,194,135
Full sample of vacancies	6,564,962
↪ Valid municipality and occupational identifier	5,495,499
↪ Not from staffing and recruitment agencies	5,129,293
↪ Not from a past military service occupation	5,127,671
↪ Not from a past crafts and related trades workers occupation	4,833,230
↪ Not from a past agriculture, forestry or fishery occupation	4,813,773

Note: See Section 4.4 for details on the sample selection.
Source: Authors' own calculations.

4.5 Definitions

Unemployment, Vacancies and Matches

The stock of vacancies (V_t) is taken from the number of active vacancies registered by NAV at each point in time, and the number of unemployed (U_t) is the stock of individuals registered as full-time unemployed in the unemployment register from NAV at each point in time. We follow Hall and Schulhofer-Wohl (2018) and define a labor market match at time t on the individual level ($m_{i,t}$) as a transition from unemployment at time t to employment at time $t+1$ (commonly denoted as a U-E transition).

While the unemployed individuals actively search for a job (a requirement of receiving unemployment benefits from NAV), the pool of matches in the labor market also encompasses individuals making a transition from one establishment to another (job-to-job transition) and individuals making a transition from outside the labor force into employment. Despite these two flows into employment being substantial, the effective number of job seekers from these two labor market states are not directly observable, and therefore we do not include them in our analysis. While the Labor Force Survey from Statistics Norway has unemployed, employed and non-employed respondents answer whether they actively search for a job or not, the sample size of the survey is too small for the purpose of this paper.

Worker Types

Worker types are defined based on observable characteristics on the individual level including educational level, gender, age group and unemployment spell duration. Educational level is split into three distinct levels (primary schooling, high school and college/university), age group is split into six distinct levels (16–19 years, 20–24 years, 25–39 years, 40–54 years, 55–66 years and 67–74 years), and unemployment spell duration is split into four distinct levels (2–4 weeks, 4–12 weeks, 12–18 weeks, 18 weeks or more). In total, we therefore have $J = 144$ well-defined worker types.

Local Labor Markets

The local labor markets are defined based on the geographical region of a county and the first digit of the four-digit occupational code. Based on the 11 counties and 7 one-digit occupational codes, we have $I = 77$

well-defined local labor markets. What truly constitutes a local labor market is difficult to define, and will most likely be an endogenous outcome that can best be derived using the flows of workers across establishments (Nimczik, 2018). However, we choose to use the administrative boundaries and the occupational classification, as deriving the endogenous local labor markets is beyond the scope of this paper.

5 Descriptive Statistics

5.1 Unemployed

Table 2 shows descriptive statistics of the unemployed individuals across the three education levels with respect to age, gender, past occupation before the unemployment spell, and duration of the unemployment spell. On average, the college-educated unemployed are the oldest (with an average age of 40.5 years) and a little over half of the unemployed are female. Most come from a past occupation as professionals (35 percent), an occupational group which includes teachers, doctors, lawyers and financial analysts. The unemployed with high school or primary school as the highest level of education come mainly from past occupations as service and sales workers (29 percent), but a large share of the primary school-educated unemployed also come from elementary occupations (25 percent), an occupational group which includes cleaning staff, kitchen helpers and other low-level laborer occupations.

The incidence of unemployment is higher the lower the education level of the unemployed, with an average of 27,760 unemployed per month from the lowest educated group versus an average of 12,546 unemployed per month from the highest educated group. The primary school-educated unemployed also have slightly longer unemployment spell durations than the two other educational groups (108 days).

Table 2: Individual-Level Characteristics of Unemployed, by Education Level

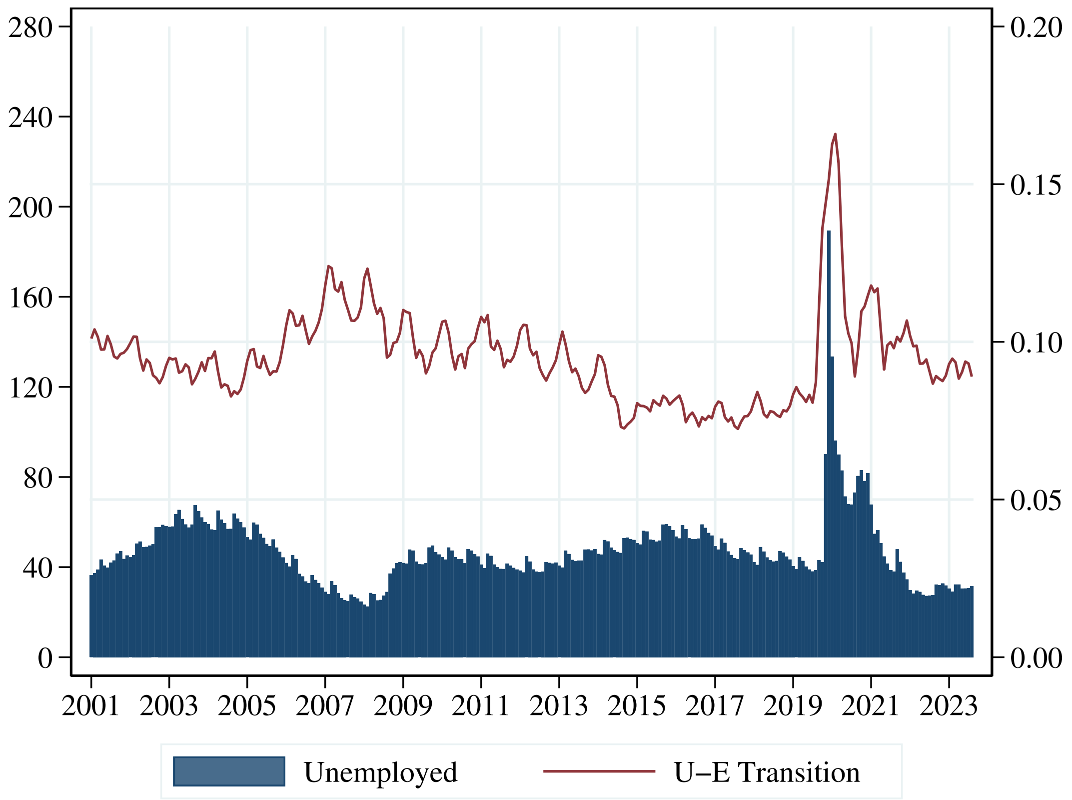
	College/university	High school	Primary
Age (years)	40.5	37.8	38.3
Female (share)	0.52	0.46	0.46
Past occupation (share):			
↪ Managers	0.11	0.08	0.05
↪ Professionals	0.35	0.08	0.05
↪ Technicians and associate professionals	0.18	0.18	0.12
↪ Clerical support workers	0.09	0.11	0.10
↪ Service and sales workers	0.16	0.29	0.29
↪ Plant and machine operators and assemblers	0.04	0.13	0.15
↪ Elementary occupations	0.07	0.13	0.25
Duration of unemployment (median number of days)	101	97	108
Number of individuals (average per month)	12,546	15,669	27,760

Note: See Section 4.4 for details on the sample selection.
Source: Authors' own calculations.

5.2 Matching Rates

Figure 2 on the next page shows the share of individuals going from unemployment at time t to employment at time $t+1$ (f_t), as well as the stock of unemployed individuals at each time t (U_t). As expected, the number of unemployed varies across the business cycle, falling from 2004 and onwards until 2008 when there was a surge in unemployment due to the financial crisis. After another peak in the time following the the oil price fall in 2015, unemployment sharply rose again as a result of the restrictions put in place to contain the coronavirus pandemic in 2020, before falling sharply again. Over the time period we study, 9.5 percent of all unemployed at time t make a transition to employment at time $t+1$. This is in line with the corresponding average monthly U-E rates reported for several other European countries (Engbom, 2022), as well as what has previously been found for Norway (Johansen, 2015).

Figure 2: Stock of Unemployed and Transition Rate from Unemployment to Employment (U-E).



Note: U-E transition refers to transitions from unemployment at time t to employment at time $t+1$ (measured on the right-hand vertical axis), while unemployed refers to the stock of unemployed individuals (measured in 1,000 on the left-hand vertical axis). The plotted U-E series is the four-month simple moving average.
Source: Authors' own calculations using data from Statistics Norway.

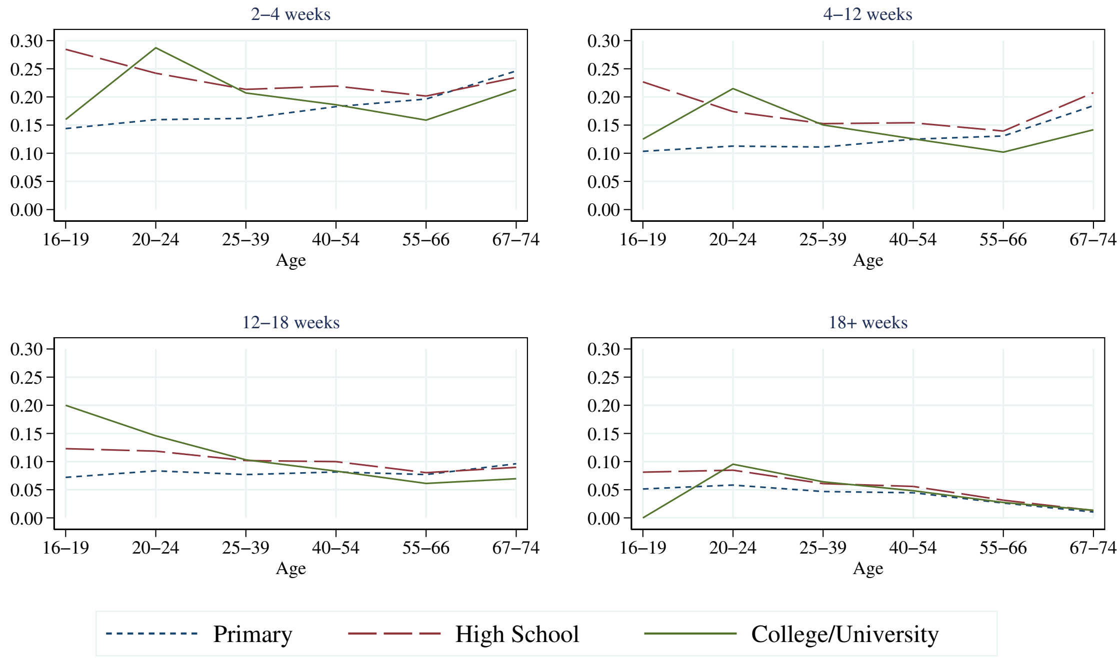
The four panels in Figure 3 on the next page show the U-E transition rates by age group, education level and unemployment spell duration. In general, the U-E transition rates are monotonically decreasing by unemployment spell duration. From Figure 3, we see that there is no distinct difference across education groups, but the transition from unemployment to employment for spells lasting more than 12 weeks seems to, on average, be falling by age.

5.3 Vacancies

The distribution of posted vacancies across occupations is shown in Table 3 on the next page, with the associated median duration of the vacancy posting (measured in days). On average per month, most vacancies postings are posted within the occupational groups consisting of professionals (14,615) and service and sales workers (10,981). Per vacancy posting, the average number of vacancies is highest within service and sales work and plant and machine operators and assemblers (2.0). The median number of days the vacancy posting is active is between 15–19 days depending on the occupation.

Figure 4 shows the evolution of the stock of vacancies and the duration of vacancies over the time period we study. The peak number of vacancies posted occurred at the start of 2008, right before the financial crisis, and in 2019, right before the coronavirus pandemic. However, comparing the movements of the stock of vacancies from 2017 and onwards with earlier periods must be interpreted with some caution due to the

Figure 3: U-E Transition Rates, by Age, Education and Unemployment Spell Duration.



Note: The education groups are defined in the note for Table 2.
Source: Authors' own calculations using data from Statistics Norway.

data challenges noted in Section 4. The duration of the vacancies has steadily increased over time, but with a drop during the coronavirus pandemic and a subsequent increase after that. Over the whole period that we study, the average vacancy duration was 18.2 days, with a median of 17 days.

Table 3: Postings, Vacancies and Duration, by Occupation

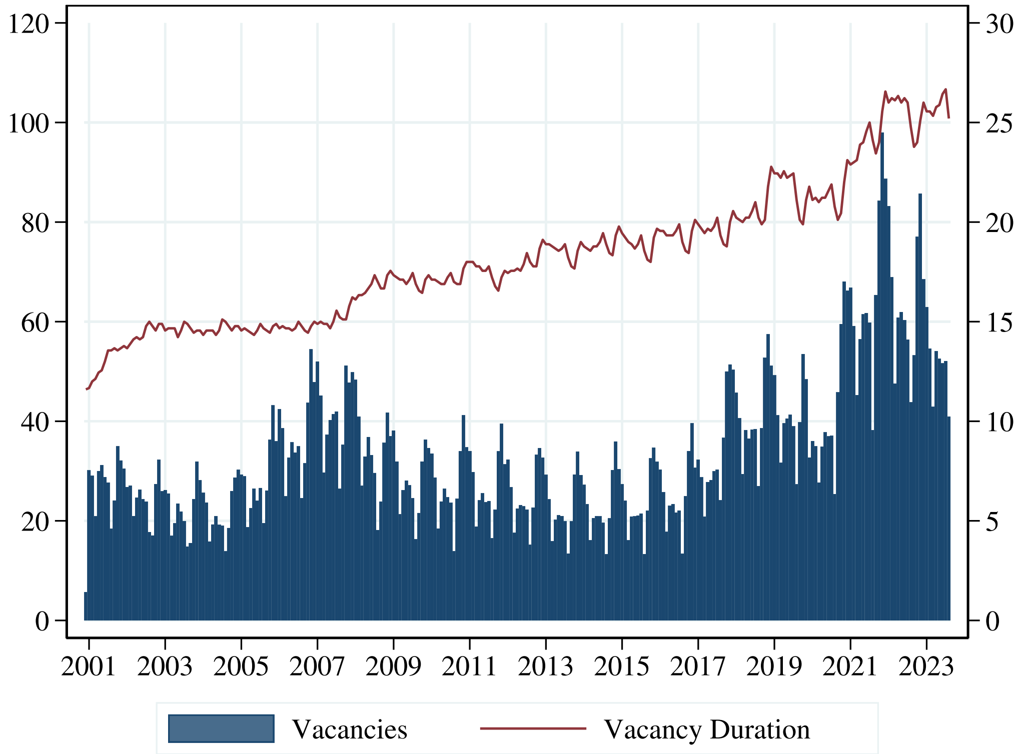
	Average number of vacancies per month	Vacancies per posting	Median posting duration (days)
Occupation of posted vacancy:			
↪ Managers	2,809	1.1	19
↪ Professionals	14,615	1.5	19
↪ Technicians and associate professionals	5,033	1.5	18
↪ Clerical support workers	1,805	1.5	17
↪ Service and sales workers	10,891	2.0	18
↪ Plant and machine operators and assemblers	1,797	2.0	16
↪ Elementary occupations	3,226	1.8	15

Note: See Section 4.4 for details on the sample selection.
Source: Authors' own calculations using data from the Norwegian Labour and Welfare Administration (NAV).

5.4 Geographical Dispersion of Labor Market Outcomes

Figure 5 on the next page shows the average matching rate ($\overline{f}_t$) and average labor market tightness ($\overline{\theta}_t$) for each of the 11 counties that constitute one part of the local labor market definition. We see that there is a large variation in both the labor market tightness and matching rates across the counties, with the average matching rate over the sample period being lowest in the Oslo region (7.7 percent) and highest in Nordland (12.6 percent). In terms of average labor market tightness over the sample period, this is lowest in Vestfold and Telemark (with approximately two job seekers per posted vacancy) and highest in Nordland (with approximately one job seeker per posted vacancy).

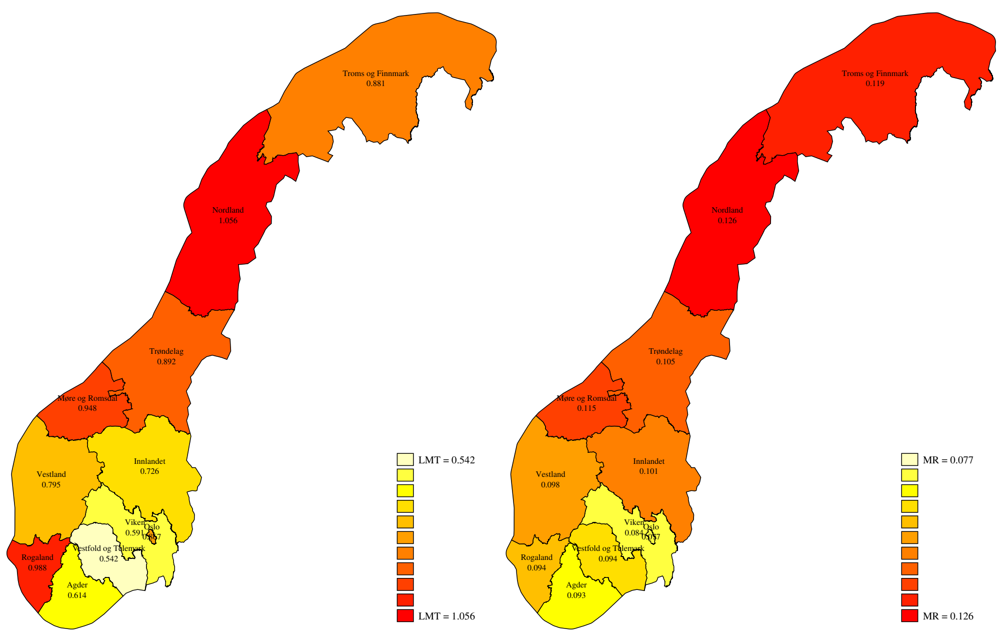
Figure 4: Stock of Vacancies and Duration of Vacancies.



Note: The stock of vacancies (measured on the left-hand vertical axis) is calculated using the start and stop dates of the vacancy postings, while vacancy duration (measured on the right-hand vertical axis) is calculated as the median vacancy duration of the stock of vacancies at each point in time. The plotted vacancy duration is the four-month simple moving average. See Section 4.4 for details on the sample selection.
Source: Authors' own calculations using data from the Norwegian Labour and Welfare Administration (NAV).

Figure 5: Geographical Dispersion of Labor Market Outcomes Across Counties.

(a) Labor Market Tightness (b) Matching Rate



Note: The maps show the average labor market tightness in Panel (a) and the average matching rate in Panel (b) over the sample period 2001–2023 for each of the 11 counties. LMT in Panel (a) refers to labor market tightness, while MR in Panel (b) refers to matching rate.
Source: Authors' own calculations using data from Statistics Norway.

6 Estimation

6.1 Estimating Equations

In this subsection, we first estimate the aggregate matching function. Next, we conduct separate estimations of occupation-specific matching functions. Finally, we introduce a matching function with heterogeneity.

Aggregate Matching Function

Taking the logarithm of Equation (2) and assuming that the matching efficiency parameter A_t can be decomposed into a constant term and an error term ($A_t = A \times \varepsilon_t$), the estimation equation for the aggregate matching function can be written as:

$$\log(f_t) = \underbrace{\log(A)}_{\beta_0} + \underbrace{(1-\sigma)}_{\beta_1} \log(\theta_t) + \underbrace{\log(\varepsilon_t)}_{\zeta_t}. \tag{13}$$

Here, $\beta_1 = 1 - \sigma$ is the aggregate elasticity of transitions from unemployment to employment with respect to labor market tightness. In order to control for seasonal variation, we include indicator variables for calendar month, allow for seasonal variation to vary across the pre- and post-2015 period, and include indicator variables for the data break in the linked employer-employee data going from December 2014 to January 2015. In addition, we control for the break in data for vacancy flow from August 2017 and onwards, as well as an erroneous coding of the number of vacancies in 2020 by NAV. These indicator variables are included as the vector τ_t in the error term, such that $\zeta_t = \tau_t + \varepsilon_t$.

The specification in Equation (13) is estimated using ordinary least squares (OLS), where we restrict the estimation period from May 2001 to February 2020 to avoid using the variation from the coronavirus pandemic, which induced a government-regulated shutdown of many of the sectors and an associated increase in the number of furloughed workers.

Aggregate Matching Function with Occupational Heterogeneity

To allow for heterogeneity across occupations, we rewrite the matching function in Equation (1) to allow for both the matching efficiency parameter and the elasticity to vary across occupations (here denoted by the subscript i), such that the system of estimation equations becomes:

$$f_{it} = A_{it} \theta_{it}^{1-\sigma_i}. \tag{14}$$

Taking the logarithm of Equation (14) and assuming that the matching efficiency parameter A_{it} can be decomposed into a constant term and an error term ($A_{it} = A_i \times \varepsilon_{it}$), the occupation-specific matching functions can be estimated using the following form:

$$\log(f_{it}) = \underbrace{\log(A_i)}_{\alpha_i} + \underbrace{(1-\sigma_i)}_{\beta_{1i}} \log(\theta_{it}) + \underbrace{\log(\varepsilon_{it})}_{\zeta_{it}}. \tag{15}$$

The parameters of Equation (15) are the same as before, with the exception of the fixed effect for occupation (α_i). To avoid assuming uncorrelated error terms for each occupation-specific equation, we estimate the system of occupation-specific equations using seemingly unrelated regression (SUR), and compare it to separate OLS regressions of Equation (15) for each occupation $i \in \{1, \ldots, I\}$.

Matching Function with Heterogeneity Across Labor Markets and Worker Types

The estimating equation for the matching function with heterogeneity across both local labor markets and worker types in Equation (6), here expressed as a log-likelihood function, is as follows, where y_{jit} equals 1 if an individual (subscripts for individuals dropped for notational ease) of worker type j from a local labor market i finds a job over time t and zero otherwise:

$$\ell(\beta, A_i, \sigma) = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\left[(1-y_{jit})\log(1-F_{jit}) + y_{jit}\log(F_{jit})\right]$$
$$\text{where}$$
$$F_{jit} = 1-\exp\left(-A_i\exp(X_{jit}\beta)\left(\sum_{j=1}^{J}\frac{U_{jit}}{U_{it}}\exp(X_{jit}\beta)\right)^{\sigma-1}\theta_{it}^{1-\sigma}\right) \tag{16}$$

In the vector X_{jit} in Equation (16) we include separate indicator variables for educational level (3 levels), gender (2 levels), age group (6 levels) and unemployment duration (4 levels) as described in Section 4.5.

6.2 Estimation Results

Estimation Results for Aggregate Matching Function

Table 4 shows the results from estimating Equation (13) with OLS, where we sequentially add the indicator variables for data breaks described in Section 6.1. The preferred specification in Column (4) indicates that the elasticity of the matching rate with respect to the labor market tightness is 0.160. This estimate implies that a 10 percent increase in the labor market tightness is associated with an 1.6 percent increase in the matching rate in the labor market.

Table 4: Aggregate Matching Function, Results

	Matching rate (log)			
	(1)	(2)	(3)	(4)
Labor market tightness (log)	0.122	0.132	0.130	0.160
	(0.023)	(0.016)	(0.017)	(0.018)
Indicators for month	✓	×	×	×
Indicators for month, pre- and post-2015	×	✓	✓	✓
Indicators for 2014M12 and 2015M1	×	×	✓	✓
Indicators for 2017M8–2017M12	×	×	×	✓
Adjusted R^2	0.565	0.790	0.792	0.805
Number of observations (T)	226	226	226	226

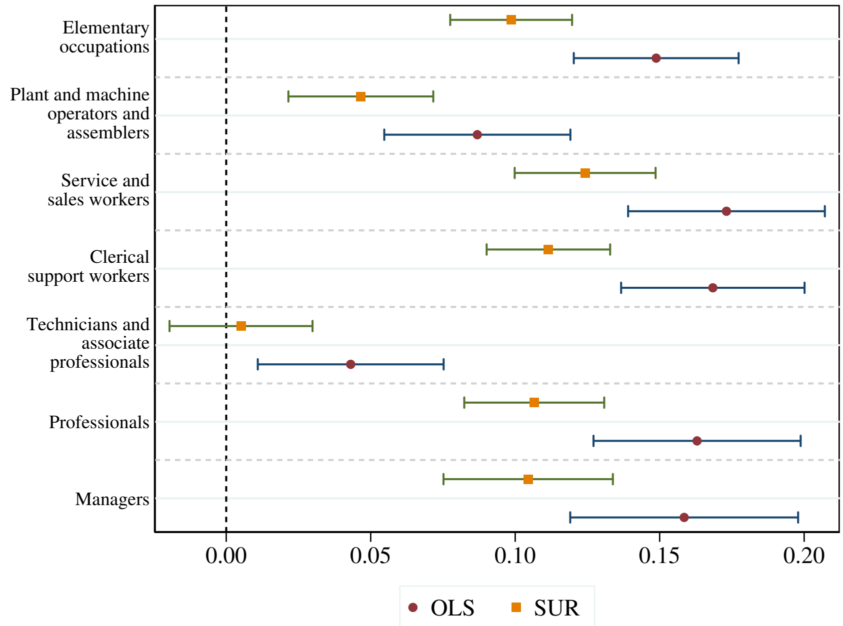
Note: Results from estimation of Equation (13) with OLS, with robust standard errors in parentheses. Estimation period is May 2001 to February 2020.
Source: Authors' own calculations.

The preferred estimate in Column (4) in Table 4 is lower than what both Barnichon and Figura (2015) and Cui (2023) find for the United States using a standard OLS approach and a Cobb-Douglas functional form (at 0.330 and 0.237, respectively), and lower than what Turrell et al. (2018) and Pizzinelli and Speigner (2017) find for the United Kingdom using a standard OLS approach and a Cobb-Douglas functional form (at 0.367 and 0.333, respectively). The elasticity estimate is however within the range of elasticities non-parametrically estimated by Lange and Papageorgiou (2020) on data from the United States, which is estimated between 0.15 and 0.30, and only slightly lower than what Jung et al. (2023) find for Germany (0.25)

Estimation Results for Aggregate Matching Function with Occupational Heterogeneity

Figure 6 below shows the results from estimating the system of occupation-specific matching functions, given by Equation (15), with SUR and the results from estimating Equation (15) using OLS for each occupation i separately, and shows large heterogeneity across occupations. The elasticity of the matching rate with respect to the labor market tightness using the SUR approach ranges from 0.005 for technicians and associate professionals (not statistically significant at conventional levels) and up to 0.124 for sales and service workers.

Figure 6: Aggregate Matching Function, by Occupation.



Note: Results from estimation of Equation (15) using seemingly unrelated regression (SUR) and Equation (15) using OLS for each occupation separately. Occupation is defined as either the first digit of the 4-digit occupational code of the posted vacancy or as the first digit of the 4-digit past occupational code of the unemployed individual. Capped lines show the 95 percent confidence intervals based on robust standard errors. Table A1 in Appendix A.3 reports the point estimates and standard errors shown in the figure.
Source: Authors' own calculations using data from Statistics Norway.

Estimation Results for Matching Function with Heterogeneity

As a first pass, we estimate the log-likelihood function in Equation (16) when there is no worker heterogeneity in terms of search effort, but where there are distinct local labor markets. The results from this exercise is reported in Column (2) of Table 5 on the next page, and shows a elasticity of 0.200. This is higher than the OLS estimate of the aggregate elasticity of 0.160, which is reported in Column (1) in the same table. When including the measure of search intensity of workers (i.e. the worker heterogeneity) in Column (3), the elasticity estimate decreases to 0.108. The reduced elasticity estimate when adding controlling for worker heterogeneity is consistent with an upward bias in the OLS estimate of the matching function, and accords with what both Lisauskaite (2022) and Barnichon and Figura (2015) find.

The results from estimating the matching function with heterogeneity can first be summarized by considering the individual-level characteristics that determine the search effort in Equation (8). The results indicate that the higher educated are more likely to find a job, and that matching decreases monotonically by age. Male unemployed are more likely to find a job, according to the estimates. Finally, the duration of the unemployment spell is negatively associated with the matching rate (and monotonically so), reflecting the established result of negative duration dependence often found in the literature, see e.g. Røed and Zhang (2005). These results are illustrated in Figure A8 in Appendix A.4.

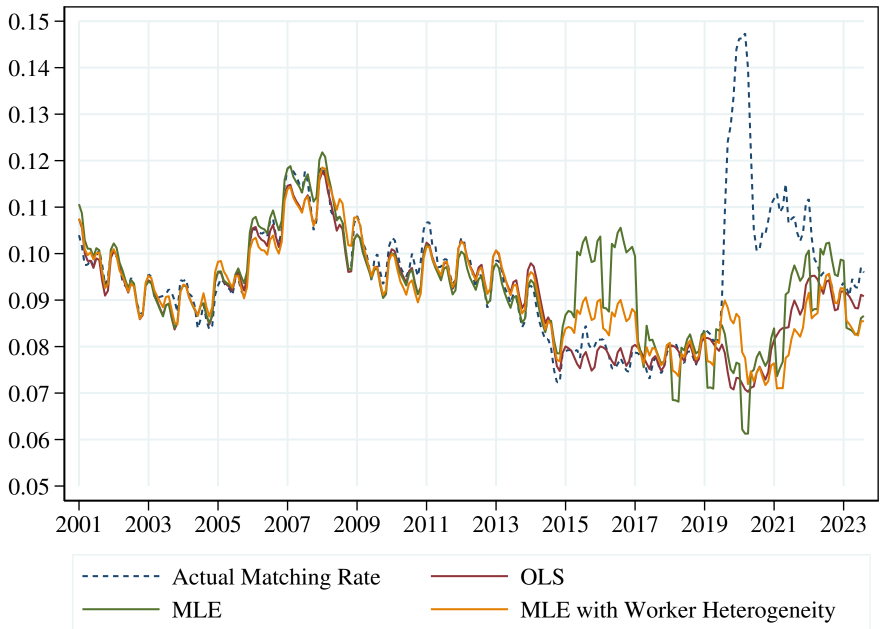
Table 5: Matching Function, OLS and Maximum Likelihood Estimation (MLE)

Dependent variable (method)	f_t (OLS) (1)	F_{jit} (MLE) (2)	F_{jit} (MLE) (3)
Labor market tightness (log)	0.160	0.200	0.108
	(0.018)	(0.002)	(0.002)
Indicators for months and data breaks	✓	✓	✓
Local labor markets	×	✓	✓
Search intensity	×	×	✓
Log-likelihood	×	-3,153,380	-2,993,346
Number of observations	226	10,298,090	10,298,090

Note: Column (1) shows the results from estimation of Equation (13), with robust standard errors in parentheses. Column (2) and Column (3) show the results from estimation of Equation (16), with robust standard errors in parentheses clustered at the individual level. For Column (1), the number of observations is the number of time periods (months), while for Column (2)–(3) the number of observations is the number of monthly observations of unemployed individuals.
Source: Authors' own calculations.

Figure 7 below shows the predicted matching rate from the OLS estimation in Equation (13), the maximum likelihood estimation in Equation (16), and the actual matching rate in data. The predicted series follow the data closely until the onset of the coronavirus pandemic (the end of the in-sample prediction in February 2020), where the matching rate became substantially higher than predicted. The exception is the period 2015–2017, where the MLE estimates implied a much higher matching rate than in the data, with the OLS estimate being much closer. From Figure 7 it is also worthwhile noting that for most of the out-of-sample predictions, the predicted matching rate converges back to the actual matching rate from July 2022, and closely align for the rest of sample period.

Figure 7: Aggregate Matching Function, Predicted and Actual Matching Rates.



Note: Results from estimation of Equation (13) with OLS, estimation of Equation (16) with maximum likelihood without and with worker heterogeneity, and the actual matching rate (dashed line). The plotted series are the four-month simple moving average.
Source: Authors' own calculations using data from Statistics Norway.

7 Decomposition of Aggregate Matching Efficiency

To decompose the changes in the aggregate matching efficiency (A_t), we use the approximation derived by Barnichon and Figura (2015) in a similar framework as ours:

$$\log(m_t) = \log(A_t) + (1-\sigma)\log(\theta_t) \tag{17}$$

where

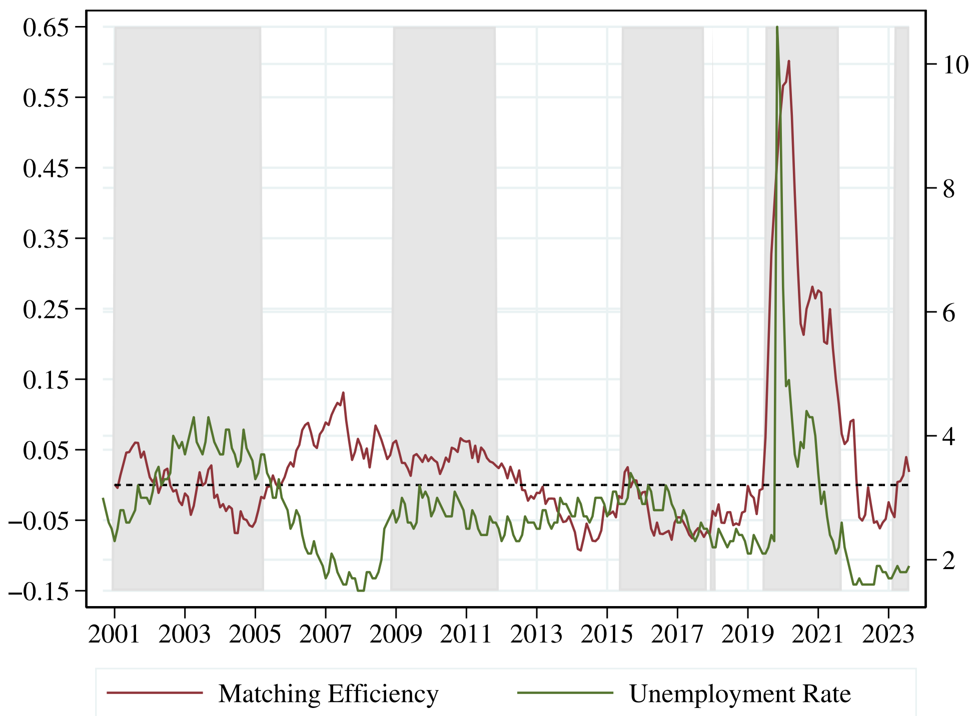
$$A_t \simeq A_0 \left(1 + A_t^s + A_t^m - \frac{\sigma(1-\sigma)}{2}\operatorname{var}\left(\frac{\theta_{it}}{\theta_t}\right)\right). \tag{18}$$

The terms A_t^s and A_t^m in Equation (18) capture the composition effects on the aggregate matching rate from (i) the change in the composition of the unemployed (A_t^s) and (ii) the change in the distribution of unemployed across local labor markets with different average matching efficiencies (A_t^m). The third term in Equation (18) captures the effect of dispersion across local labor markets on the aggregate matching rate. The composition effects in Equation (18) are defined as follows:

$$\begin{aligned} A_t^s &= \sigma \sum_{i,j} \frac{U_{jit}}{U_t} \sum_k \beta_k \left(x_{jit}^k - \bar{x}^k\right) \\ A_t^m &= \sum_i \frac{U_{it}}{U_t} \left(\frac{A_i}{A_0} - 1\right) \end{aligned} \tag{19}$$

The evolution of the aggregate matching efficiency A_t is shown in Figure 8, where we also plot the periods in which the mainland GDP growth in Norway was below its long-run trend growth level (GDP gap) as well as the unemployment rate from NAV, so as to illustrate the evolution over the business cycle.[2]

Figure 8: Evolution of Aggregate Matching Efficiency over the Business Cycle.



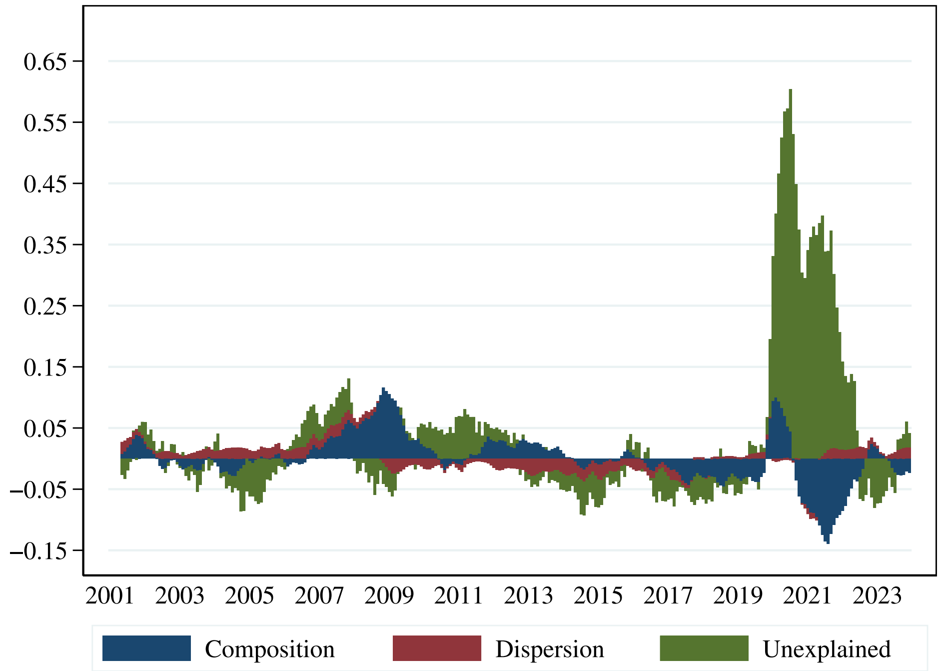
Note: The aggregate matching efficiency, defined in Equation (18), is measured on the left-hand side, while the unemployment rate is measured in percent on the right-hand side. The shaded gray areas indicate periods where the mainland GDP growth was below its long-run trend growth level. The plotted matching efficiency is the four-month simple moving average.
Source: Authors' own calculations using data from Statistics Norway.

[2] The GDP gap is calculated as the difference between the mainland GDP growth rate and the trend growth rate of mainland GDP, with the latter estimated using an Hodrick-Prescott filter (with $\lambda = 40{,}000$ for the quarterly data), but such that the trend is not directly affected by the development of economic activity during the pandemic in 2020–2021 (Statistics Norway, 2025).

Figure 8 indicates that the evolution of the matching efficiency is counter-cyclical, with a correlation of -0.334 between the GDP gap and the matching efficiency in the data. However, if we restrict attention to the period in which the matching function is estimated (before March 2020), the correlation in the data is 0.169, which indicates that the matching efficiency is pro-cyclical, as in Barnichon and Figura (2015).[3]

The evolution of the aggregate matching efficiency is also shown in Figure 9, decomposed into the composition effects (A_t^s and A_t^m), the dispersion effect ($(\sigma(1-\sigma)/2)\,\mathrm{var}(\theta_{it}/\theta_t)$) and other movements in the matching efficiency unexplained by the model. The fraction of the movements in the matching efficiency unexplained increases after the estimation sample period (February 2020), as expected from Figure 7.

Figure 9: Decomposing the Evolution of Aggregate Matching Efficiency.



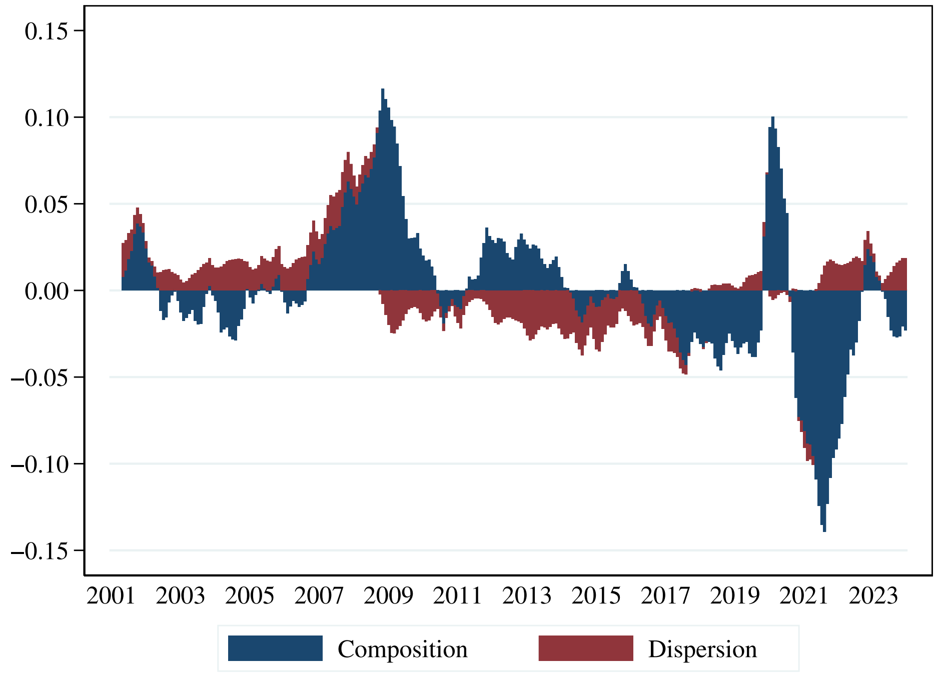
Note: The plotted series are the four-month simple moving averages.
Source: Authors' own calculations using data from Statistics Norway.

The explained evolution of the aggregate matching efficiency decomposed into the composition effect and the dispersion effect (i.e. disregarding the unexplained movements) is shown in Figure 10 on the next page, and illustrates that most of the explained movement in the matching efficiency is driven by the composition of the unemployed and their search effort, and not the dispersion in labor market tightness across local labor markets. The composition effect is strongly pro-cyclical, and more so than the aggregate matching efficiency, with a correlation between the GDP gap and the composition effect of 0.340 before March 2020.

Figure 11 on the next page further decomposes the evolution of the composition effect into its subcomponents based on the observable characteristics that determine the search effort of the unemployed (age, gender, education level, and the duration of the unemployment spell), as well as the distribution of unemployed individuals across local labor markets with different average matching efficiencies. As is evident from Panel (c) in Figure 11, most of the variation in the composition effect stems from the variation in the unemployment spell duration of the unemployed individuals. This finding is similar to what Barnichon and Figura (2015) and Lisauskaite (2022) find in their analyses.

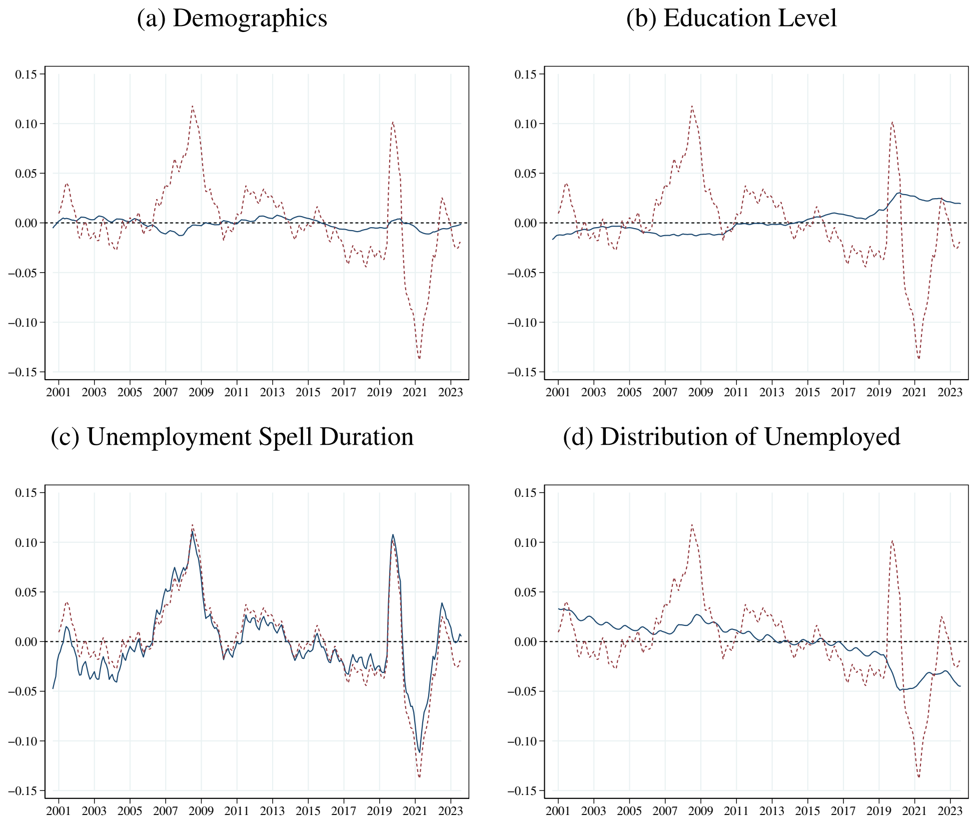
[3] See Appendix A.5 for an alternative measure of business cycle movements using the OECD-based recession indicators for Norway (Federal Reserve Bank of St. Louis, 2022).

Figure 10: Decomposing the Evolution of Explained Aggregate Matching Efficiency.



Note: The plotted series are the four-month simple moving averages.
Source: Authors' own calculations using data from Statistics Norway.

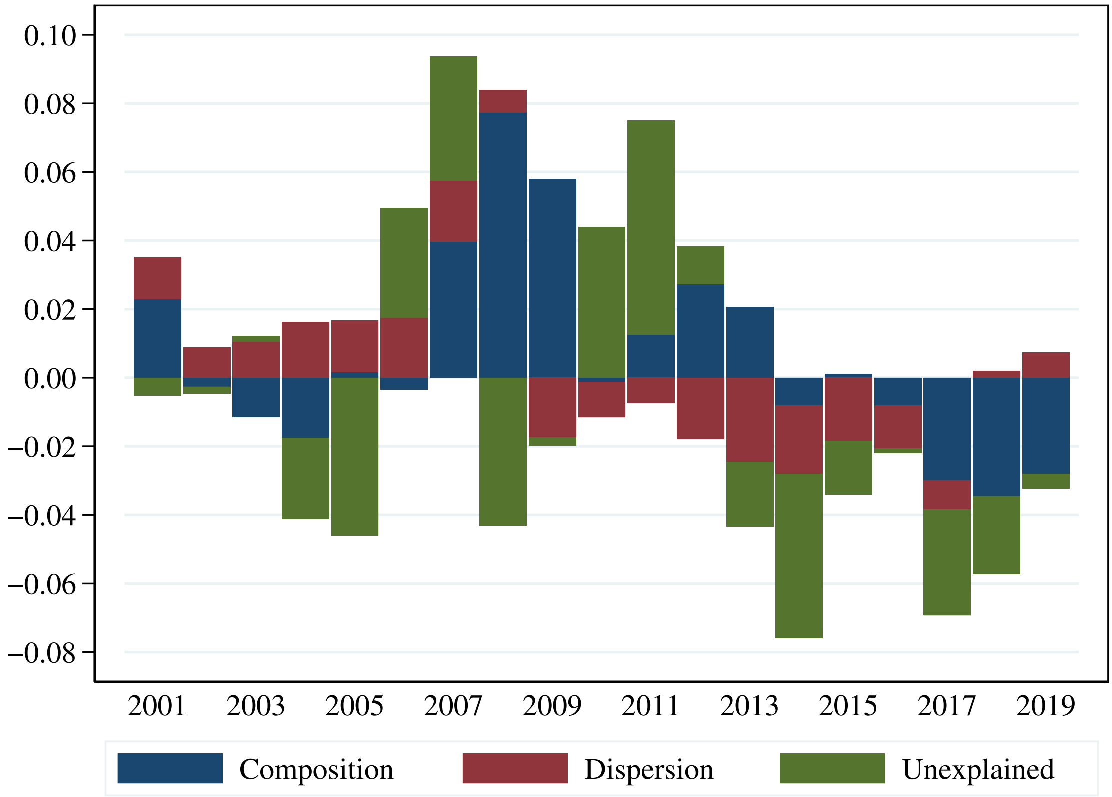
Figure 11: Decomposing the Evolution of the Composition Effect.



Note: The panels show the decomposition of the composition effect into four components: demographics, education level, unemployment duration and distribution of unemployed individuals across local labor markets. The solid lines show the contributions from each component, while the dashed line in each panel shows the total composition effect. The plotted series in all panels are the four-month simple moving average.
Source: Authors' own calculations using data from Statistics Norway.

If we focus on the period prior to the start of the coronavirus pandemic in 2020 and consider the decomposition of the matching efficiency on the annual level (measured as the average of the components over the year), a clear downward trend in the matching efficiency from 2007 to 2017 emerges, see Figure 12. While the composition of unemployed contributed positively to the matching efficiency from the financial crisis (2008–2009) and onwards to 2013, the dispersion effect has consistently contributed negatively to the matching efficiency from 2009–2017. This is to say that an increased dispersion in the matching rates across local labor markets over time has contributed to a lower aggregate matching probability.

Figure 12: Decomposing the Evolution of Explained Aggregate Matching Efficiency, by Year.



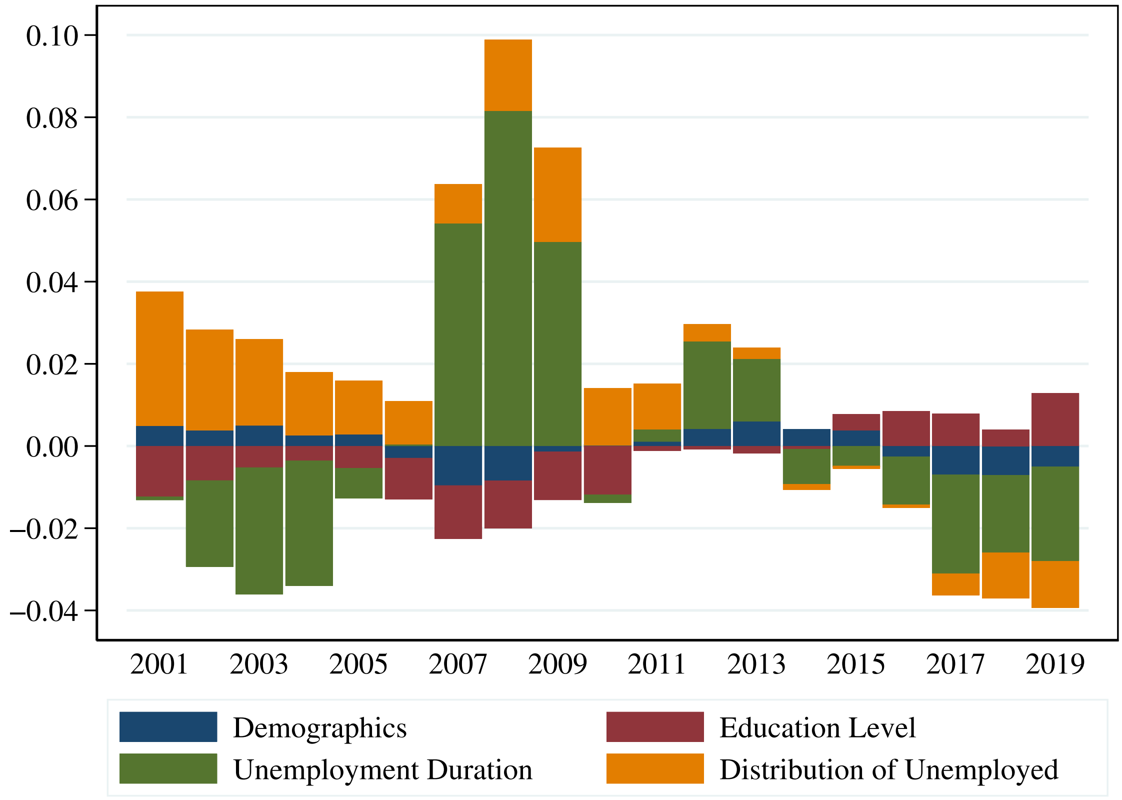
Note: The plotted annual series are the averages of the unadjusted monthly series by year.
Source: Authors' own calculations using data from Statistics Norway.

If we consider the annual-level effect of the components of the composition effect on the matching efficiency in Figure 13 on the next page, we find that the while the dispersion in matching rates across local labor markets drove down the matching rate in the period 2009–2017, there seems to be no such negative effect of the distribution of unemployed across local labor markets with different matching efficiencies. In other words, the effect from the local labor markets on the downward trend in the aggregate matching efficiency over the period 2009–2017 stems from a differential evolution of the local labor market conditions (in terms of the number of unemployed and vacancies), and not the changing distribution of unemployed across inherently different local labor markets (in terms of matching efficiency of the local labor market).

8 Counterfactual Evolution of Matching Efficiency

As two counterfactual exercises, we investigate the evolution of the predicted matching rates when we fix either the labor market tightness or the search effort at the levels before two distinct periods of economic downturns in Norway: (i) the financial crisis of 2008 and (ii) the oil price crisis of 2014.

Figure 13: Decomposing the Evolution of the Composition Effect, by Year.



Note: The plotted annual series are the averages of the unadjusted monthly series by year.
Source: Authors' own calculations using data from Statistics Norway.

In the first counterfactual exercise, the predicted matching rate varies over time only due to variation in the search effort over time, with the labor market tightness for each local labor market set to the value in the month preceding the economic downturn in question:

$$f_t = A_i s_t^{\sigma} \overline{\theta^{1-\sigma}} \tag{20}$$

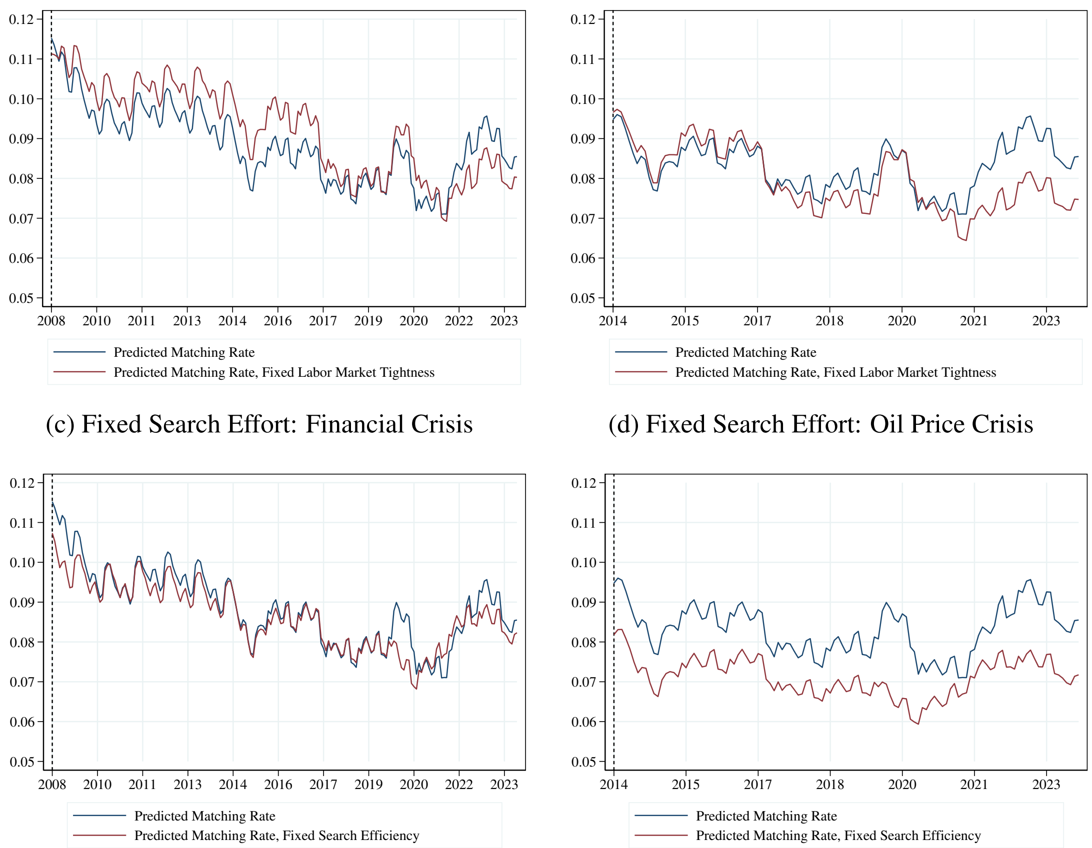
In the second counterfactual exercise, the predicted matching rate varies over time only due to variation in labor market tightness across, with the search effort of unemployed individuals set to the average in the month preceding the economic downturn in question:

$$f_t = A_i \overline{s^{\sigma}} \theta_t^{1-\sigma} \tag{21}$$

Figure 14 on the next page shows the actual matching rate in the data, the predicted matching rate of the full model and the predicted matching rate when we shut down either the labor market tightness channel (upper panels) or the search effort channel (lower panels) for the financial crisis of 2008 and the oil price crisis of 2014 (Panel (a) and (c) and Panel (b) and (d), respectively).

While shutting down the search effort channel induces a (negative) level-shift in the predicted matching rate, the pattern is largely the same over time as when allowing it to vary. The exception is 2019, where the deviation indicates that changes to the pool of unemployed individuals compared to the pre-downturn periods led to a a higher matching rate. When fixing the labor market tightness, no clear pattern emerges in terms of the counterfactual matching rate versus the actual matching rate.

Figure 14: Counterfactual Matching Rates.



(a) Fixed Labor Market Tightness: Financial Crisis (b) Fixed Labor Market Tightness: Oil Price Crisis

(c) Fixed Search Effort: Financial Crisis (d) Fixed Search Effort: Oil Price Crisis

Note: The panels show the evolution of the matching rate under various counterfactual assumptions in terms of fixing the labor market tightness (upper panels) and fixing the search effort (lower panels). We define the financial crisis as having started in September 2008, and the oil price crisis in June 2014. The plotted series in all panels are the four-month simple moving average.
Source: Authors' own calculations using data from Statistics Norway.

9 Conclusion

Using detailed micro-data on individuals and establishments for the period 2001–2024, we find that the decrease in the matching rate (the transition rate from unemployment to employment) in the period 2007–2019 coincided with a decrease in the matching efficiency in the labor market over the same time period. Decomposing the evolution of the matching efficiency for this period, we find that while the composition of unemployed individuals contributed positively to the evolution of the matching rate up until 2013, mainly through the pool of unemployed having shorter unemployment spell durations. At the same time, the dispersion of matching rates across local labor markets, defined as broad occupational categories by county, consistently contributed negatively to the matching efficiency over the time period 2007–2019.

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Appendix

A.1 Sample Construction

If an individual is registered as a wage earner in the linked employer-employee register and full-time unemployed in the unemployment register at the same time, we define the individual as being full-time unemployed. Primary education of an individual is defined as NUS categories 0, 1, 2, 3 and 9, high school is defined as NUS categories 4 and 5, and college/university is defined as NUS categories 6, 7 and 8. We drop unemployment spells with a valid past occupational code whose first digit is 0 (military occupations), 7 (craft and related trades occupations) or 6 (skilled agriculture, forestry and fishery occupations). In terms of vacancies, we drop vacancies posted by establishments with the industry code 78.200 (staffing and recruitment agencies), and vacancies with valid occupational code whose first digit is 0 (military occupations), 7 (craft and related trades occupations) or 6 (skilled agriculture, forestry and fishery occupations).

A.2 Details on the Decomposition of Matching Efficiency

In terms of the distribution of unemployed across local labor markets (A_t^m), note that we can solve for the matching efficiency in the local labor market i (A_i) using Equation (3) and the identity $F_{jit} = 1 - \exp(f_{jit})$, which also gives the average (weighted) matching efficiency across the local labor markets (A_0):

$$\begin{aligned} A_i &= \frac{m_{it}}{V_{it}^{1-\sigma}(s_{it}U_{it})^{\sigma}} \\ &= \frac{m_{it}}{s_{it}^{\sigma}\theta_{it}^{1-\sigma}} \\ &= \frac{-\log(1-F_{jit})}{s_{it}^{\sigma}\theta_{it}^{1-\sigma}} \\ A_0 &= \frac{1}{T}\sum_{i,t}\frac{U_{it}}{U_t}A_i. \end{aligned} \tag{A1}$$

From our data and the estimated parameters, the decomposition can therefore be written as:

$$\log(m_t) \simeq \log\left(\hat{A}_0\left(1+\hat{A}_t^s+\hat{A}_t^m-\frac{\hat{\sigma}(1-\hat{\sigma})}{2}\text{var}\left(\frac{\theta_{it}}{\theta_t}\right)\right)\right)+(1-\hat{\sigma})\log(\theta_t) \tag{A2}$$

where

$$\begin{aligned} \hat{A}_t^s &= \hat{\sigma}\sum_{i,j}\frac{U_{jit}}{U_t}\sum_k\hat{\beta}_k\left(x_{jit}^k-\bar{x}^k\right) \\ \hat{A}_t^m &= \sum_i\frac{U_{it}}{U_t}\left(\frac{\hat{A}_i}{\hat{A}_0}-1\right) \\ \hat{A}_i &= \frac{-\log(1-F_{jit})}{\hat{s}_{it}^{\hat{\sigma}}\theta_{it}^{1-\hat{\sigma}}} \\ \hat{A}_0 &= \frac{1}{T}\sum_{i,t}\frac{U_{it}}{U_t}\hat{A}_i \\ \hat{s}_{it} &= \sum_i\frac{U_{jit}}{U_{it}}\exp\left(X_{jit}\hat{\beta}\right). \end{aligned} \tag{A3}$$

A.3 Additional Tables

Table A1 shows the estimation results for the matching function with occupational heterogeneity, estimated with seemingly unrelated regression (SUR) and ordinary least squares (OLS).

Table A1: Matching Function with Occupational Heterogeneity, Results

	Matching rate (log)	
	SUR	OLS
	(1)	(2)
Managers	0.104	0.158
	(0.015)	(0.020)
Professionals	0.107	0.163
	(0.012)	(0.018)
Technicians and associate professionals	0.005	0.043
	(0.013)	(0.016)
Clerical support workers	0.111	0.168
	(0.011)	(0.016)
Service and sales workers	0.124	0.173
	(0.012)	(0.017)
Plant and machine operators and assemblers	0.047	0.087
	(0.013)	(0.016)
Elementary occupations	0.099	0.149
	(0.011)	(0.015)
Indicators for month	✓	✓
Indicators for month, pre- and post-2015	✓	✓
Indicators for 2014M12 and 2015M1	✓	✓
Indicators for 2017M8–2017M12	✓	✓

Note: Results from estimation of Equation (15) using seemingly unrelated regression (SUR) and Equation (15) using OLS for each occupation separately.
Source: Authors' own calculations.

A.4 Additional Figures

Figure A1 compares the micro data from NAV with the aggregate stock of vacancies published by Statistics Norway, which is based on a survey that also captures informally posted vacancies (e.g. through coworkers, family, friends). The stock of vacancies published by Statistics Norway is based on a representative survey of approximately 8,000 establishments, who report their stock of vacancies in the reference period each quarter (last week in middle month of the quarter). From this survey, the population-level stock of vacancies is estimated using a stratified model with 140 strata (industry$\times$size).

Figure A2 shows the transition rates from non-employment to employment (N-E) and the job-to-job-transition rates (E-E).

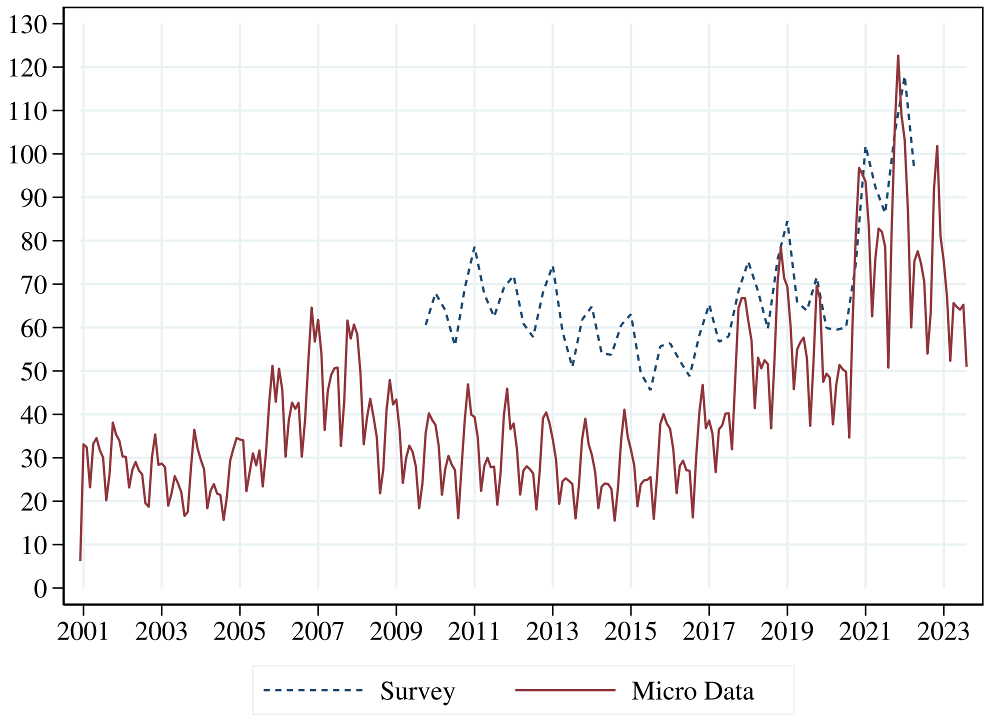
Figure A3 and Figure A4 show the distributions of the duration of unemployment spells and vacancy postings, respectively.

In Figure A5, the distribution of start and stop dates of employment relationships over the period 2001–2014 is shown.

The number of posted vacancies from the NAV micro data which we use relative to the estimated vacancies from Statistics Norway (which also includes non-posted vacancies) for the construction industry is low, see Figure A6 and Figure A7 for comparison of vacancy stocks from the two data sources across industries.

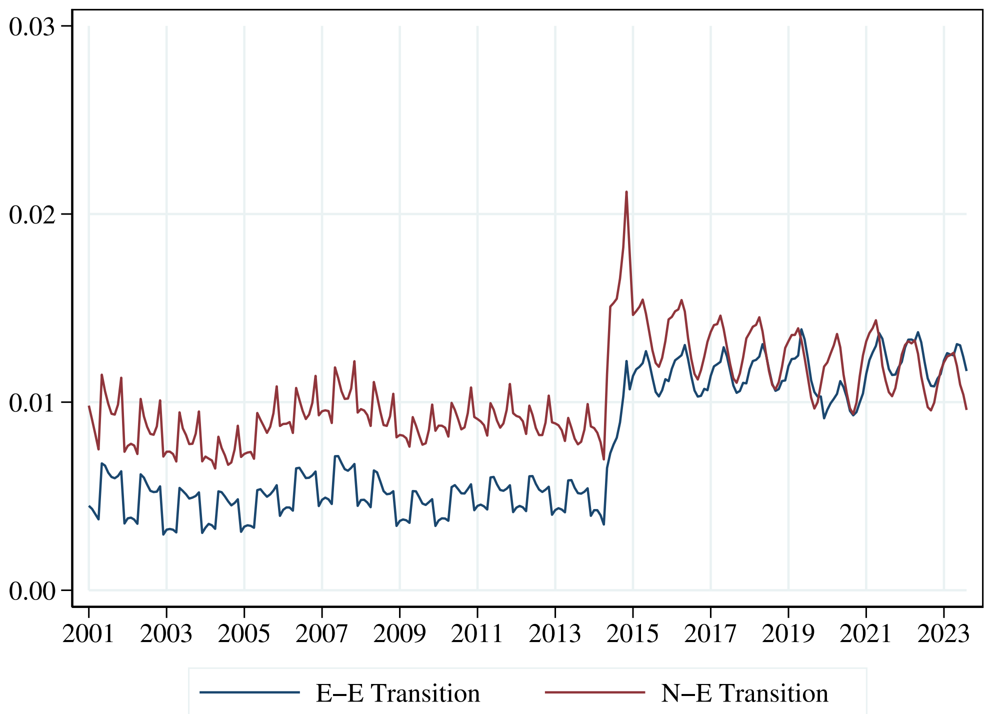
Figure A8 shows the estimated coefficients for the search effort of unemployed individuals.

Figure A1: Stock of Vacancies. Comparison of Data Sources. Measured in Thousands.



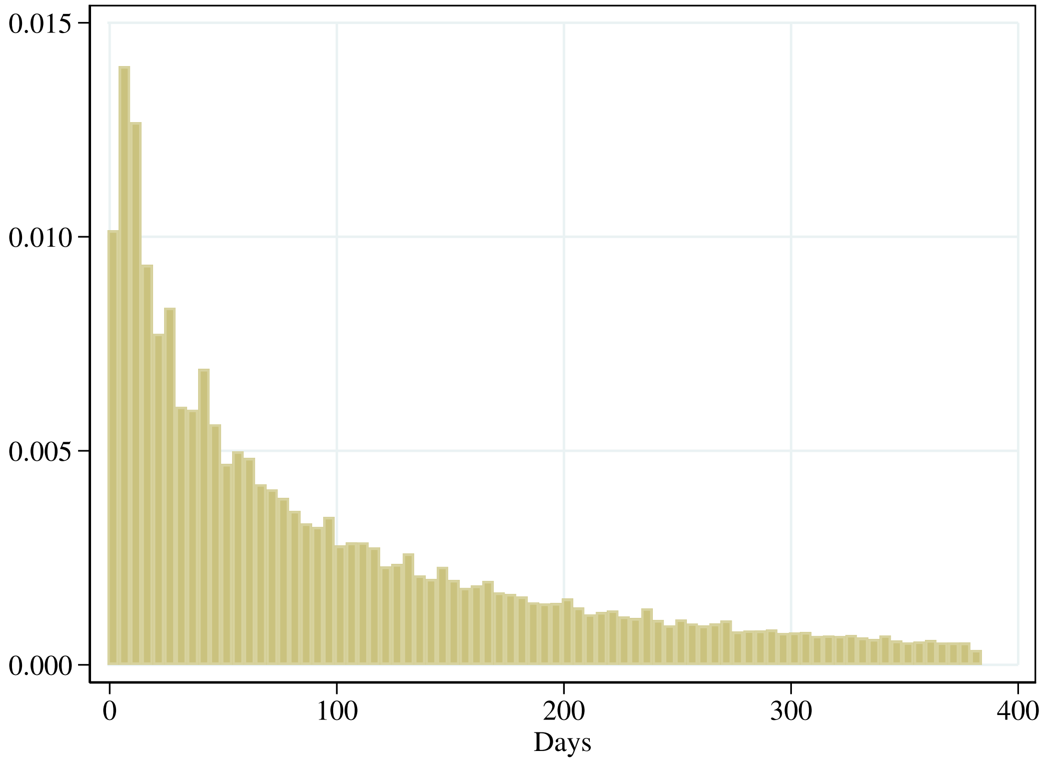
Note: The vacancy stocks are measured in thousands.
Source: Authors' own calculations using data from the Norwegian Labour and Welfare Administration and Statistics Norway.

Figure A2: Transition Rates, Non-Employment to Employment (N-E) and Job-to-Job Transitions (E-E).



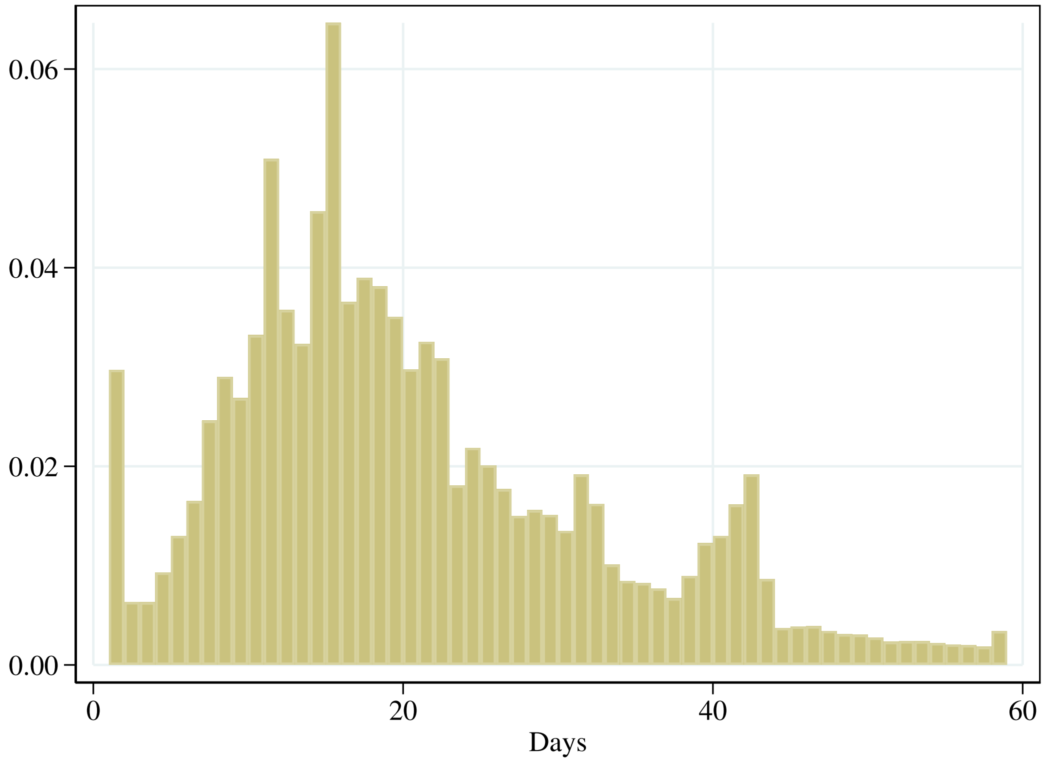
Note: N-E transition refers to non-employment to employment, while E-E transition refers to transitions from one employer to another, defined as change of establishment. The plotted N-E and E-E series are the four-month simple moving averages.
Source: Authors' own calculations using data from Statistics Norway.

Figure A3: Duration of Unemployment Spells.



Note: The figure is restricted to unemployment spell durations below the 90th percentile for the sake of exposition.
Source: Authors' own calculations using data from Statistics Norway.

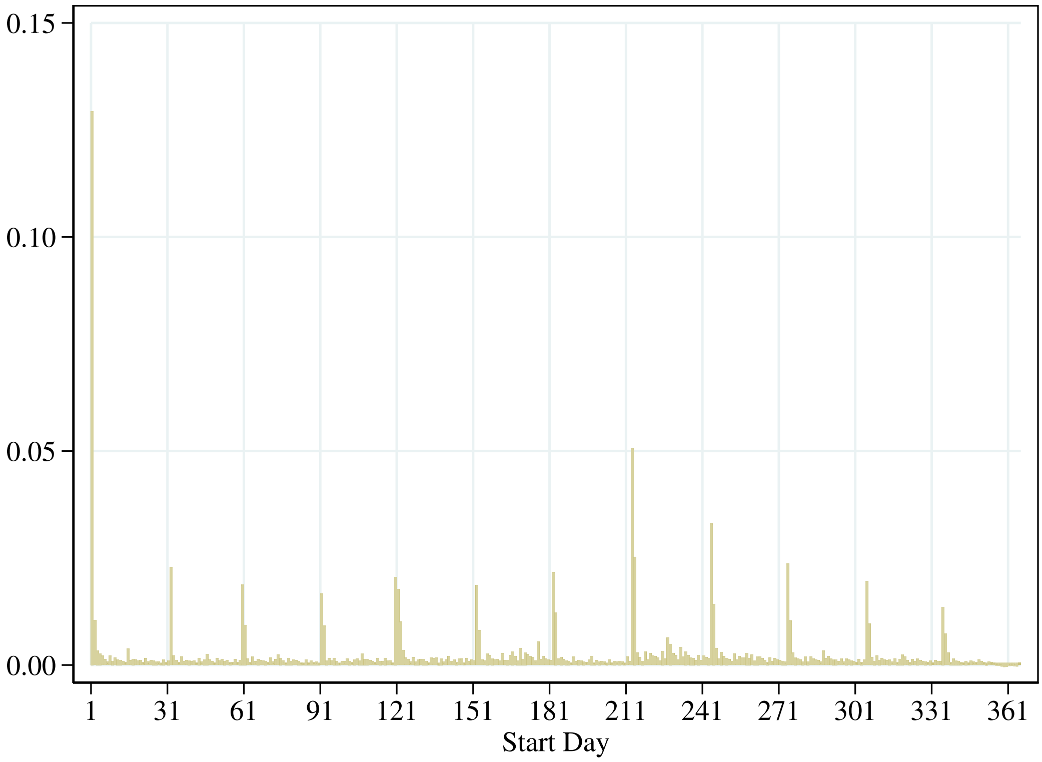
Figure A4: Duration of Vacancy Postings.



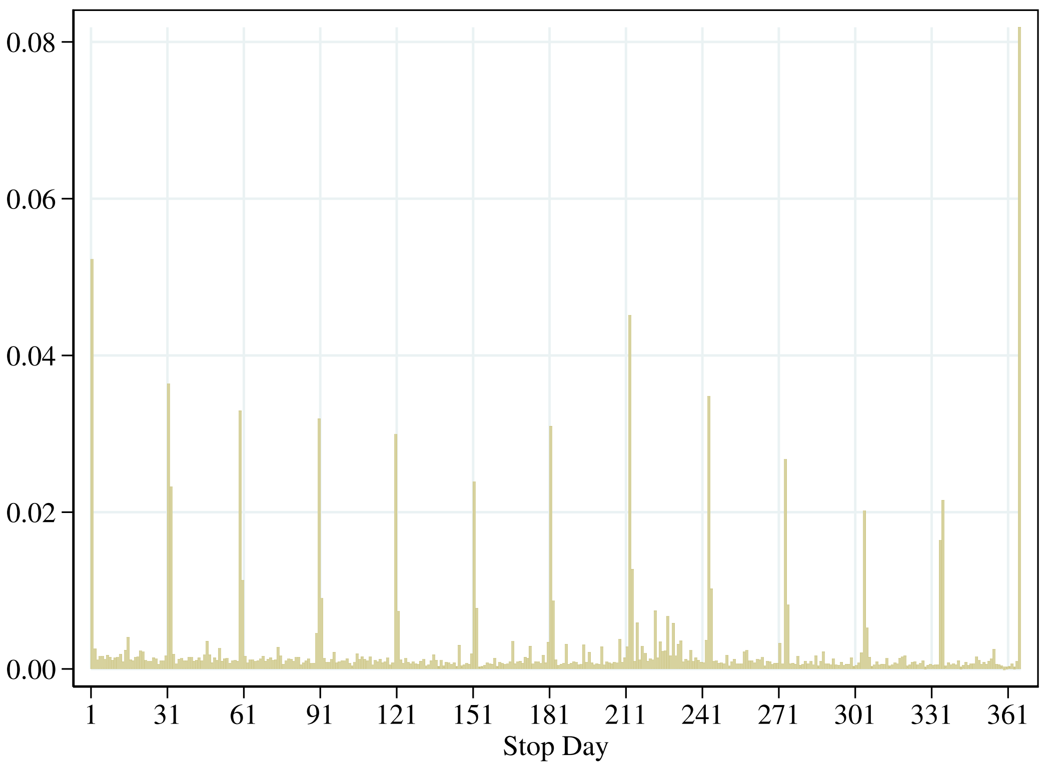
Note: The figure is restricted to vacancy posting durations below the 95th percentile for the sake of exposition.
Source: Authors' own calculations using data from the Norwegian Labour and Welfare Administration (NAV).

Figure A5: Distribution of Start and Stop Dates, 2001–2014.

(a) Distribution of Start Dates



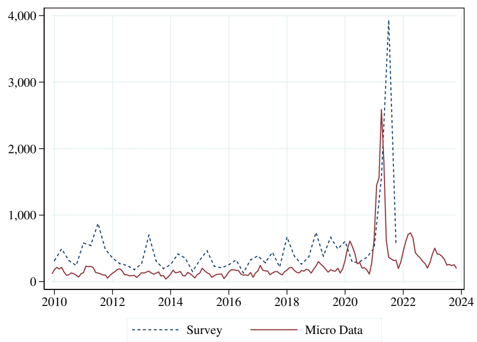
(b) Distribution of Stop Dates



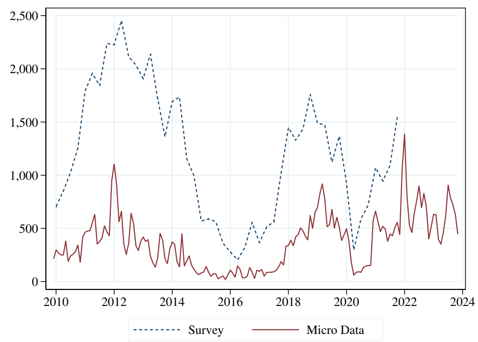
Note: The figure shows the distribution of start and stop dates in the linked employer-employee data sets for the period 2001–2014, where the individual has positive wage income and positive number of contracted working hours.
Source: Authors' own calculations using data from Statistics Norway.

Figure A6: Stock of Vacancies. Comparison of Data Sources. Measured in Thousands. By Industry.

(a) Agriculture, Forestry and Fishing

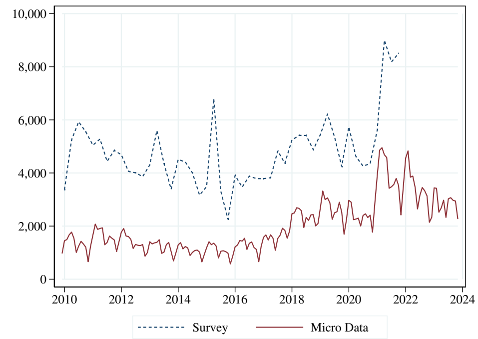


(b) Mining and Quarrying



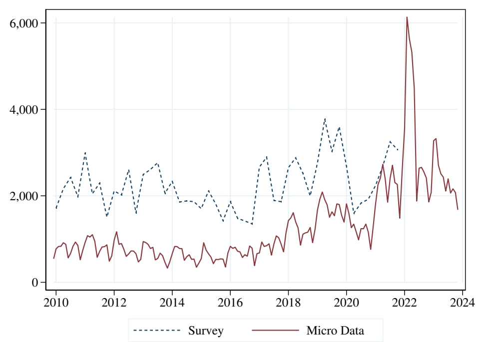
(c) Manufacturing

(d) Construction

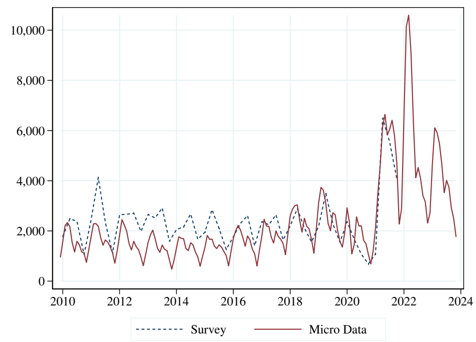


(e) Wholesale and Retail Trade

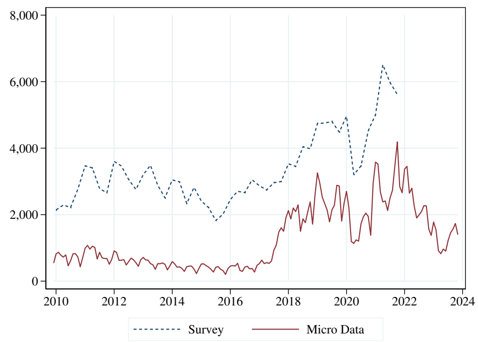
(f) Transportation and Storage



(g) Accommodation and Food Service Activities



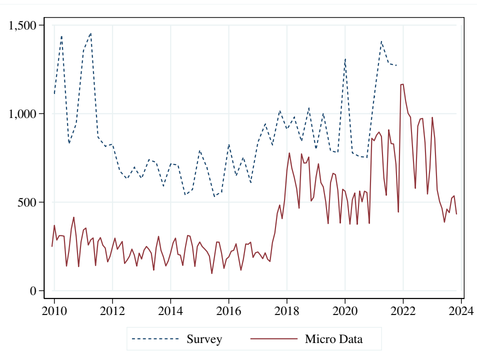
(h) Information and Communication



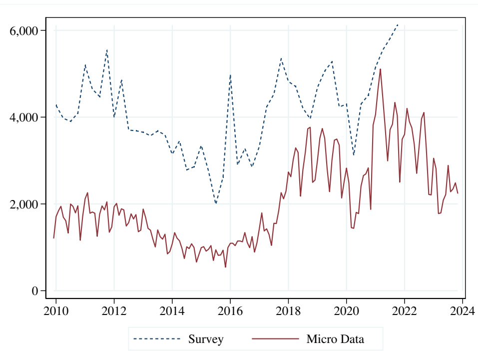
Source: Authors' own calculations using data from the Norwegian Labour and Welfare Administration (NAV) and Statistics Norway.

Figure A7: Stock of Vacancies. Comparison of Data Sources. Measured in Thousands. By Industry.

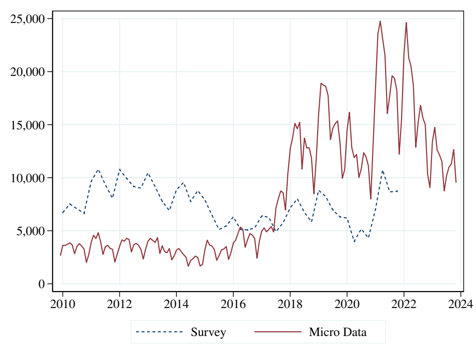
(a) Financial and Insurance Activities



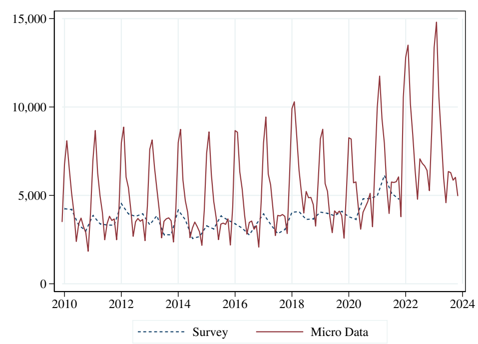
(b) Professional, Scientific and Technical Activities



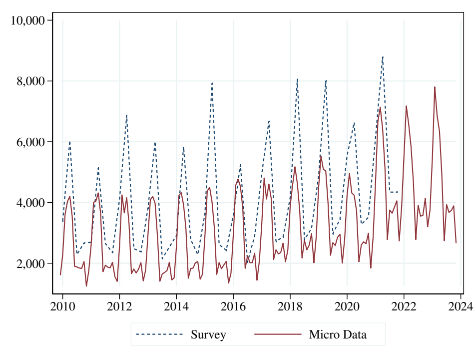
(c) Administrative and Support Service Activities



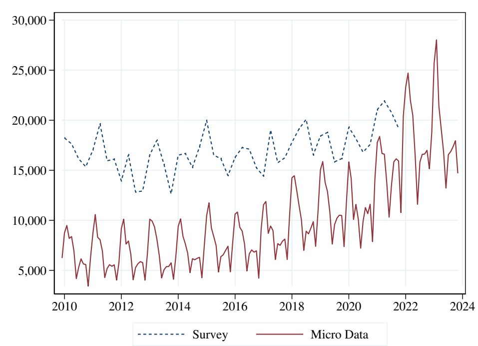
(d) Public Administration and Defence



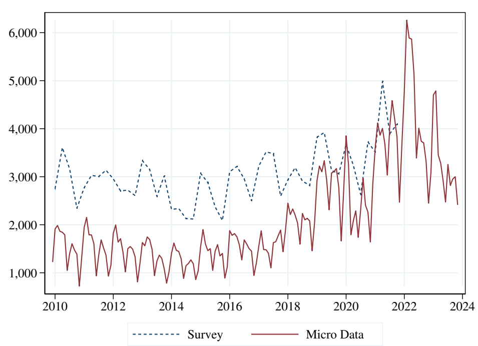
(e) Education



(f) Human Health and Social Work Activities



(g) Other



Source: Authors' own calculations using data from the Norwegian Labour and Welfare Administration (NAV) and Statistics Norway.

Figure A8: Search Effort and Individual Characteristics.

Note: Results from estimation of Equation (11) using maximum likelihood estimation. The reference categories are as follows: (i) education level = primary schooling, (ii) age groups = 16–19 years, (iii) gender = male, (iv) unemployment duration = 2–4 weeks. Capped lines show the 95 percent confidence intervals based on robust standard errors
Source: Authors' own calculations using data from Statistics Norway.

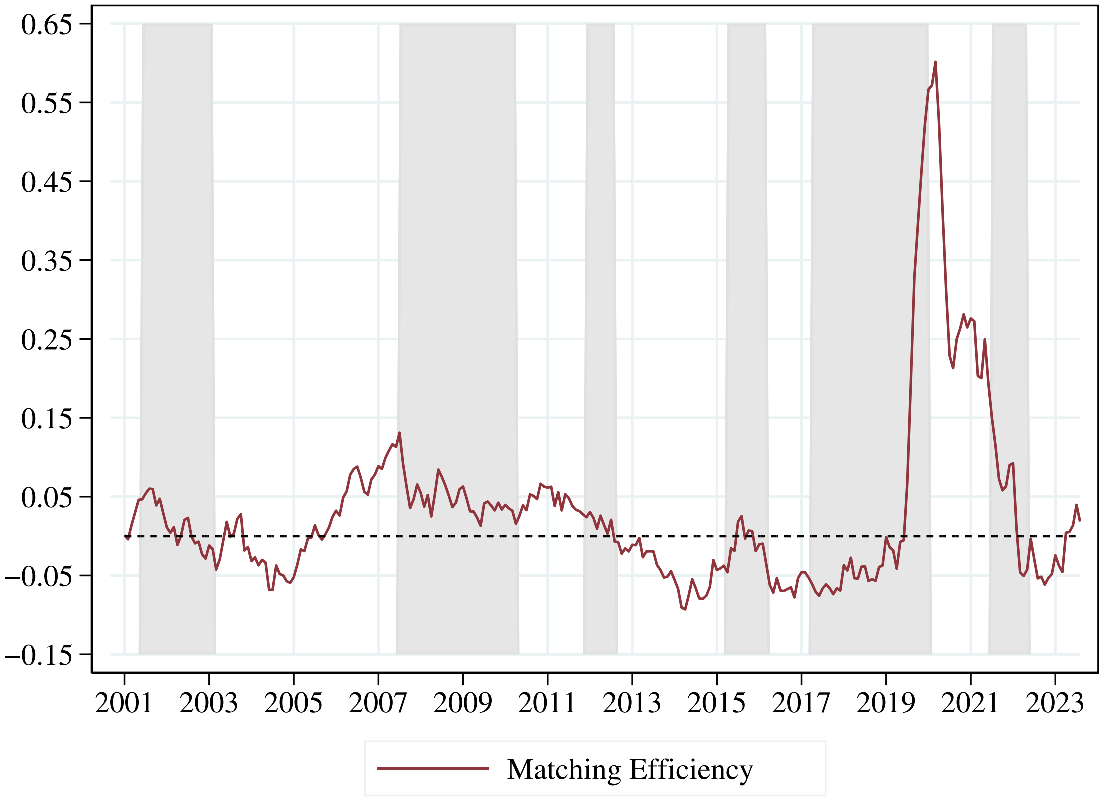
A.5 Alternative Measure of Business Cycle Movements

Instead of using the GDP gap, Figure A9 on the next page shows the evolution of the matching rate when using the OECD-based recession indicators for Norway (Federal Reserve Bank of St. Louis, 2022), which is available until September 2022.

Figure A9 indicates that the evolution of the matching efficiency is almost acyclical, with a correlation of 0.004 between the no-recession indicator and the matching efficiency in the data. If restricted to the period in which the matching function is estimated (before March 2020), the correlation in data is -0.067.

When only considering the composition effect, we find that it is counter-cyclical with a correlation between the no-recession indicator and the composition effect of -0.091 before March 2020.

Figure A9: Evolution of Aggregate Matching Efficiency over the Business Cycle, OECD-Based Indicator.



Note: The aggregate matching efficiency is defined in Equation (18). The shaded gray areas indicate periods that the OECD-based recession indicators (Federal Reserve Bank of St. Louis, 2022) define as a recession. The plotted matching efficiency is the four-month simple moving average.
Source: Authors' own calculations using data from Statistics Norway.