Estimating Matching Efficiency with Variable Search Effort

Andreas Hornstein and Marianna Kudlyak*

May 21, 2015
PRELIMINARY AND INCOMPLETE.

Abstract

Not accounting for heterogeneity in the effectiveness of job search and, specifically, for endogenous variation in search effort, can lead to biased estimates of not only matching efficiency but also matching elasticity in the aggregate matching function. Modeling search effort as a constant elasticity function of the aggregate matching rate, we show the following. First, to a first order approximation, the cyclicality of search effort is identified only conditional on the elasticity of the aggregate matching function. The estimated search effort is pro-cyclical for low values of matching elasticity and counter-cyclical for high values of matching elasticity. Second, changes in the aggregate matching efficiency are identified up to a positive scalar. We find little cyclicality but a noticeable downward trend for the estimated aggregate matching efficiency following the Great Recession. Finally, if we were to ignore heterogeneity in the endogenous variation in search effort and write the average transition rate as a constant elasticity function of the standard labor market tightness measure, the implied measured matching elasticity is identified and is approximately equal 0.35, independently of the underlying 'true' matching elasticity.

Key words: Matching efficiency. Search effort. Matching elasticity. Aggregate matching function.

*Federal Reserve Bank of Richmond, P.O. Box 27622, Richmond VA 23261, USA. Email: andreas.hornstein@rich.frb.org and marianna.kudlyak@rich.frb.org. The authors thank Yongsung Chang for helpful comments. The authors thank Marisa Reed for excellent research assistance. The views expressed here are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Richmond or the Federal Reserve System.

1. Introduction

In Diamond-Mortensen-Pissarides matching models of the labor market the matching function plays a role similar to the aggregate production function in macroeconomic models of the goods market. The matching function is a reduced form representation of how in a frictional labor market the combination of workers that are looking for employment and vacant positions that need to be filled—the inputs to the matching function—results in new matched workers and positions—the output of the matching function. For this approach, changes in how well the labor market 'works' are reflected in changes of the matching efficiency, that is, changes in meeting rates that cannot be accounted for by changes in workers looking for work or changes in open positions. The concept of matching efficiency corresponds to that of total factor productivity for the aggregate production function. Similar to the measurement of changes in total factor productivity, measured changes in matching efficiency depend on the measures of the inputs to the matching function.

In the recovery from the 2007-09 recession, unemployment declined slower than vacancy postings by firms increased. The differential response of unemployment and vacancies shows up as an upward shift of the Beveridge curve.[1] In the matching function framework, an upward shift of the Beveridge curve reflects a decline in matching efficiency, that is, the labor market works less well at bringing searching workers and vacancies together. Various attempts have been made to attribute the apparent decline in matching efficiency to the mismeasurement of inputs to the matching function.[2]

Our approach builds on this line of research and recognizes the importance of the correct measurement of the inputs to the matching function. Specifically, we account for heterogeneity in the effectiveness of job search of various groups of job seekers. However, in contrast to the existing literature, our approach allows for the effectiveness of job search to encompass both the persistent exogenous differences among groups as well as the differences in endogenous variation in search effort. Not accounting for the heterogeneity in endogenous variation in search effort leads to the biased estimates of not only aggregate matching efficiency but also of the matching elasticity parameter in the aggregate matching function.

Motivated by the standard search and matching model (e.g., Pissarides (2000)), we model search effort as a constant elasticity function of the aggregate transition rate determined by the matching function. Given this modeling choice, we show the following. First, to a first order approximation, the groups' search effort elasticities with respect to the aggregate

[1]The Beveridge curve is the negative empirical relationship between the unemployment rate and the vacancy posting rate which, for the most part, appears to be quite stable.

[2]For example, Şahin Song, Topa, and Violante (2012), Veracierto (2011), Elsby, Michaels, and Ratner (forthcoming), Kroft, Lange, Notowidigdo and Katz (2013), Hall and Schulhofer-Wohl (2015), and Davis, Faberman, and Haltiwanger (2013).

transition rate, on the one hand, and the elasticity of the aggregate matching function, on the other hand, are not separately identified. This then implies that our estimates of the cyclicality of search effort depend on the elasticity of the matching function: search effort is pro-cyclical (counter-cyclical) for low (high) values of the matching function elasticity. Second, the type-specific persistent effects in the effectiveness of job search are identified and the aggregate matching efficiency is identified up to a positive scalar. Third, if we were to ignore heterogeneity in search effort and write the average transition rate as a constant elasticity function of the standard labor market tightness measure, the implied measured matching elasticity is identified, albeit is independent of the underlying 'true' matching elasticity.

Given our theoretical results that groups' search effort elasticities and matching elasticity are not separately identified and that the aggregate matching efficiency is identified up to a positive scalar defined by the matching efficiency, we proceed to estimate the groups' search effort elasticities and aggregate matching efficiency contingent on a value of matching elasticity. While the procedure does not sign the cyclicality of search effort as the sign depends on the value of the matching elasticity, it delivers the estimates of the aggregate matching efficiency up to a positive scalar.

In the estimation, we define the effective search input from workers to the matching function as the transition rate weighted sum of searching workers. This yields a log-linear relation between the observable employment transition rates, vacancies, effective search effort, and an error term that includes matching efficiency. We proceed to estimate the search effort parameters and matching efficiency in two ways. The first approach involves a two-stage procedure, where we first estimate the effort elasticities using OLS and then treat the error terms as generated regressors, applying a Kalman filter to them to infer matching elasticity. This approach is straightforward, but the parameter estimates are potentially biased since the error terms are not exogenous. For the second approach, we use an extended Kalman filter to simultaneously estimate the parameters and matching efficiency.

We apply our estimation procedure to two alternative classifications of the non-employed: unemployed job seekers by duration of unemployment, and non-employed job seekers by labor force status (unemployed and out of the labor force) and gender. For the matching elasticity of 0.5, for example, the estimation for the first classification of the non-employed yields negative estimates for the search effort elasticity with respect to the aggregate matching rate, and the absolute value of search effort elasticity increases with the duration of unemployment (from -0.6 to -0.3). The estimation for the second classification of the non-employed (by labor force status and gender) also yields counter-cyclical search effort, with similar magnitude for men and women, but search effort of the unemployed being relatively less responsive to the aggregate matching rate. The two estimation procedures yield for the most part similar values for the effort elasticities, but a Monte Carlo exercise shows that while the estimates from the extended Kalman filter appear to be unbiased for both classifications of the non-employed, the two-stage OLS estimates are biased for the second classification of the non-employed.

As predicted by our theoretical results, varying the value of matching function elasticity, yields different estimates of the cyclicality of the search effort: search effort is pro-cyclical for low values and counter-cyclical for high values of matching function elasticity. The decline in the aggregate job finding rate during the Great Recession is associated with a larger decline in the aggregate matching efficiency when the search effort is counter-cyclical than when the search effort is pro-cyclical. Nevertheless, regardless of the matching function elasticity, we find a noticeable downward trend in the aggregate matching efficiency starting in 2007 and little cyclicality during the entire 2001-2013 period.

To our knowledge, ours is the first study that not only allows for heterogeneity of search efficiency in the aggregate matching function, but also estimates the cyclicality of search effort in the matching framework.[3] The closest papers to our approach are Gomme and Lkhagvasuren (forthcoming) and Hall and Schulhofer-Wohl (2015). On the theory side, Gomme and Lkhagvasuren (forthcoming) model endogenous search effort in a standard matching model with homogeneous workers. They argue that search effort is pro-cyclical based on direct evidence on search activities. They then recognize that in an environment with homogeneous job search and variable effort standard estimates of the aggregate matching elasticity reflect the true matching elasticity and the search effort elasticity. Based on evidence for the search effort elasticity from independent micro studies they recover the true matching elasticity. Hall and Schulhofer-Wohl (2015) estimate the relative search efficiency of heterogeneous searchers for an aggregate matching function as described below.

The existing evidence on the cyclicality of search effort is mixed. Using the Current Population Survey data, Shimer (2004) finds that the number of search methods used by the unemployed increases during the 2001 recession. Using the Current Population Survey and the data from the Annual Time Use Survey, Mukoyama, Patterson and Sahin (2013) find that the time spent on search is countercyclical. Gomme and Lkhagvasuren (forthcoming) argue that search effort of an individual worker is pro-cyclical and that the measured counter-cyclical average search effort is due to a composition effect. Direct measurement of search effort, however, is challenging because the number of search methods used by a job seeker or the time spent on job search can be viewed as inputs into a search effort function with

[3]The cyclicality of search effort is relevant for theories that rely on pro-cyclical search effort to amplify the volatility of vacancies and unemployment in search and matching models (for example, Costain and Reiter (2008) or Gomme and Lkhagvasuren (forthcoming)).

potentially varying output over the business cycle.[4]

A number of papers have studied how 'mismeasurement' of the aggregate matching function might affect estimates of matching efficiency. Şahin, Song, Topa, and Violante (2014) show how the potential misallocation of unemployed workers across disaggregated labor markets affects measured matching efficiency in the reduced form aggregate matching function. They derive correction factors for the imperfect aggregation and find that observed misallocations do not generate large movements in these correction factors. Veracierto (2011) broadens the measure of the worker search input to include OLF participants. Even though employment transition rates from OLF are significantly smaller than from unemployment, total transitions from OLF are significant. Veracierto therefore includes OLF non-employed as an input to aggregate worker search effort, and assumes that their search effort is reflected in their employment transition rate relative to the unemployed. Implicitly this fixes the search effort of the unemployed at one. Veracierto finds a 15% decline of matching efficiency following the recession, but broadening the measure of search input does not affect his estimate of matching efficiency. Hall and Schulhofer-Wohl (2015) and Sedlacek (2014) follow up on Veracierto (2011) allowing for different matching efficiencies across groups of employed and non-employed workers. For each group they estimate an efficiency parameter that combines matching efficiency and search intensity. In their framework aggregate matching efficiency is a weighted average of the group-specific matching efficiencies which are taken as exogenous. Based on the evidence of declining search effort with unemployment duration, Davis (2011) proposes correction factor for search effort that depends on the average duration of unemployment, and constructs the effective input of workers to the matching function as the product of total unemployment and the correction factor.[5] Kroft, Lange, Notowidigdo, and Katz (2013) generalize this approach and provide a more detailed disaggregation of the unemployed by duration, but again their approach implicitly fixes search effort for the group with the highest employment transition rate. Elsby, Michaels, and Ratner (forthcoming) survey this literature.

The rest of the paper is structured as follows. Section 2 describes the production function approach to estimating matching efficiency with heterogeneous search and variable search effort. Section 3 describes a two-stage OLS procedure and a maximum likelihood based procedure to estimate search effort elasticities contingent on the aggregate matching elasticity.

[4] Shimer (2004), Mukoyama, Patterson and Sahin (2013), and Gomme and Lkhagvasuren (forthcoming) cannot distinguish whether the estimated cyclicality of effort is a result of the cyclical change of the job seeker composition with respect to the search effort or true change in an individual worker's search effort because such a distinction requires data on worker's fixed effect.

[5] Krueger and Mueller (2011) show that time devoted to search declines with unemployment duration. Faberman and Kudlyak (2014) show that the individual number of job applications declines with search duration.

Section 4 describes the data and results for our two definitions of search groups. Section 5 concludes.

2. Production function approach

There is substantial heterogeneity in employment transition rates among the non-employed. For example, transition rates are consistently higher for short-term unemployed than for long-term unemployed. In a matching framework, one can interpret these differences in transition rates as differences in the effectiveness of job search of different groups. The effectiveness of job search encompasses group-specific search effort and (possibly group-specific) matching efficiency. Changes in the group-specific search effort represent an endogenous response to the changes in the labor market conditions. Changes in matching efficiency have to be attributed to an exogenous variation in the rate at which the non-employed find jobs.

Accounting for heterogeneity in search efficiency of the non-employed is important for measurement of the overall search effort input to the matching function and, consequently, the measured matching efficiency of the labor market. For example, if there are permanent differences in the effectiveness of job search among different groups, then compositional changes in the pool of the non-employed affect the quality of the overall search effort. The quality of the overall search effort is also affected by the changes in the groups' relative efficiency of job search, which arise either due to differences in endogenous response to the labor market conditions or due to exogenous reasons.

Figure 1 displays transition rates to employment for different groups of the non-employed.[6] The two left-hand side panels show the rates for unemployed workers with different duration of unemployment. The two right-hand side panels show the rates for the unemployed or for those out of the labor force, by gender. As can be seen, transition rates to employment decline with the duration of unemployment, increase with reported active job search (i.e., higher for the unemployed than for those out of the labor force) and tend to be somewhat higher for men than for women. The differences in the transition rates among these groups persist over time, keeping the ranking of transition rates unchanged. In addition, as the lower panels of Figure 1 show, there are systematic changes in relative transition rates. The lower left-hand side panel suggests that after the Great Recession the transition rates of the medium- and long-term unemployed declined more than those of the short-term unemployed. The lower right-hand side panel suggests that after the Great Recession transition rates of those OLF actually increased somewhat relative to the transition rate of unemployed men.

[Figure 1. Transition Rates to Employment]

[6] Section 4.1 describes calculation of the transition rates.

In the remainder of this section, we describe a simple extension of the aggregate matching function approach that allows for (1) heterogeneity in the effectiveness of job search and, specifically, for (2) unobserved endogenous variation in search effort. While an emerging literature recognizes the importance of heterogeneity in the effectiveness of search, all existing approaches attribute the heterogeneity entirely to the exogenous variation in the effectiveness of job search among different groups.[7]

Motivated by the standard search and matching approach (e.g., Pissarides (2000)), we model search effort as a constant elasticity function of the aggregate transition rate determined by the matching function. Given this modeling choice, we show the following. First, to a first order approximation, the groups' search effort elasticities with respect to the aggregate transition rate, on the one hand, and the elasticity of the aggregate matching function, on the other hand, are not separately identified. Second, the type-specific persistent effects in the effectiveness of job search are identified and the aggregate matching efficiency is identified up to a scalar. Finally, if we were to ignore heterogeneity in the endogenous variation in search effort and write the average transition rate as a constant elasticity function of the standard labor market tightness measure, the implied measured matching elasticity is identified, albeit is independent of the underlying 'true' matching elasticity.

2.1. Aggregate matching function with quality adjustment

There is a finite number of search types, $i \in I$, and at any point in time u_i of type i engage in search. We assume that types differ in their search effectiveness, ρ_i, and total effective search effort is

$$u^* = \sum_i \rho_i u_i. \tag{2.1}$$

Total search effort, u^*, and the number of posted vacancies, v, are the inputs to a standard matching function that determines the number of new hires, h,

$$h = e^{\kappa} v^{\alpha} \left(u^*\right)^{1-\alpha} \tag{2.2}$$

with aggregate matching efficiency, κ, and matching elasticity, $0 < \alpha < 1$. We assume that time is continuous and the aggregate matching rate, λ, is the rate at which a unit of search effort makes the transition to employment

$$\lambda = e^{\kappa} \theta^{*\alpha} \text{ and } \theta^* = \frac{v}{u^*}, \tag{2.3}$$

[7] Recent work on the aggregate matching function with heterogeneous search activity includes among others Veracierto (2011), Barnichon and Figura (forthcoming), Kroft, Lange, Notowidigdo and Katz (2014), and Hall and Schulhofer-Wohl (2015).

where θ^* is the effective market tightness. The type matching rates, λ_i, are related to the types' search effectiveness and the aggregate matching rate λ,

$$\lambda_i = \rho_i \lambda. \tag{2.4}$$

Define the average search effort, $\bar{\rho}$, as

$$\bar{\rho} = \sum_i \frac{u_i}{u} \rho_i \text{ and } u = \sum_i u_i, \tag{2.5}$$

where u is the standard input to the matching function that does not account for differences in search effectiveness. We can then rewrite the aggregate matching rate as

$$\lambda = e^{\kappa} \left(\theta^m / \bar{\rho}\right)^{\alpha} \text{ and } \theta^m = v/u, \tag{2.6}$$

where θ^m is the standard measured aggregate labor market tightness.

The standard matching function approach ignores heterogeneity in search effectiveness, and relates the average transition rate, $\bar{\lambda}$,

$$\bar{\lambda} = \sum_i \frac{u_i}{u} \lambda_i \tag{2.7}$$

to the standard measured market tightness, θ^m, i.e.,

$$\bar{\lambda} = e^{\bar{\kappa}} \left(\theta^m\right)^{\bar{\alpha}}, \tag{2.8}$$

where $\overline{\kappa}$ and $\overline{\alpha}$ are the aggregate matching efficiency and the matching elasticity, respectively, obtained from the standard approach.

Given the heterogeneity in search effectiveness, the average transition rate relates to the measured aggregate labor market tightness as follows:

$$\bar{\lambda} = e^{\kappa} \bar{\rho}^{1-\alpha} \left(\theta^m\right)^{\alpha} \tag{2.9}$$

Clearly, $\overline{\kappa}$ and $\overline{\alpha}$ in equation (2.8) are not equal to κ and α, respectively, in equation (2.9) unless $\bar{\rho} = 1$. Consequently, heterogeneity in search effectiveness across types introduces an unobserved quality adjustment that will be conflated with matching efficiency in the standard matching function approach.

2.2. Modeling variable search effort

A type's search effectiveness may change for exogenous reasons or because of endogenous effort variation. We propose to estimate the responsiveness of search effort to the aggregate state of the labor market, relating type transition rates to the aggregate transition rate. This approach is motivated by reference to the basic matching model.

A simple modification of the basic matching model allows for variation of individual search effort that is related to the aggregate employment transition rate, e.g. Pissarides (2000) or recently Gomme and Lkhagvasuren (forthcoming). Let U and W denote the value of being unemployed and employed, respectively. Then, the return on unemployment is

$$rU = b - c(\rho) + \rho\lambda(W - U),$$

where r is the rate of time discount and b is the flow return from unemployment. Devoting effort to search increases the rate at which the worker becomes employed but it comes at a cost, $c(\rho)$. Determining the optimal choice of effort is a well-defined problem if the effort cost is an increasing convex function of effort. For simplicity, assume that the cost function is of the constant elasticity variety,

$$c(\rho) = c_0\rho^v \text{ with } \nu > 1.$$

The first order condition yields the optimal search effort as

$$\rho = \lambda^{1/(\nu-1)} \left[(W - U) / (c_0\nu)\right]^{1/(\nu-1)}, \tag{2.10}$$

that is, search effort is a constant elasticity function of the aggregate transition rate.

For the basic matching model, search effort is an increasing function of the aggregate transition rate: as the marginal benefit from search increases, the worker will devote more effort to search, yielding pro-cyclical search effort. The existing evidence on the changes in search effort in response to the changes in labor market conditions (i.e., cyclicality of search effort) is mixed. For example, Shimer (2004) and Mukoyama, Patterson and Sahin (2013) argue that search effort is counter-cyclical, that is, search effort increases when unemployment increases. In contrast, Gomme and Lkhagvasuren (forthcoming) argue that search effort is pro-cyclical.

We propose to estimate a reduced form expression that relates the search intensity for each type to the aggregate matching rate, a type-fixed effect, γ_i, and a type-specific persistent component, z_{it},

$$\ln \rho_{it} = \gamma_i + z_{it} + \eta_i \ln \lambda_t. \tag{2.11}$$

The elasticity of search effort with respect to the aggregate transition rate is η_i. We do not impose any restrictions on search effort to be pro- or counter-cyclical, but we do impose the restriction that the type transition rate is a non-decreasing function of the aggregate transition rate, $\eta_i \geq -1$. Substituting for search effort from individual matching rates in equation (2.6) yields an implicit definition of the aggregate matching rate

$$\lambda = e^{\kappa} \left(\frac{\theta^m}{\sum_i \frac{u_i}{u} e^{\gamma_i + z_i + \eta_i \ln \lambda}} \right)^{\alpha}. \tag{2.12}$$

2.3. Identification

In this subsection we show that, to a first order approximation, the aggregate matching elasticity, on the one hand, and the type search effort elasticities, on the other hand, are not separately identified. Furthermore, we show that the type-specific persistent effects are identified and aggregate matching efficiency is identified up to a scalar. Finally, if we were to ignore heterogeneity in search effort and write the average transition rate as a constant elasticity function of the standard measured labor market tightness, the implied measured matching elasticity is identified.

Applying some algebra (see the appendix), we show that to a first-order approximation the aggregate transition rate is a log-linear function of measured market tightness and matching efficiency, i.e.,

$$\Delta \ln \lambda = \frac{\alpha}{1 + \alpha \bar{\eta}_0} \left(\Delta \ln \theta^m + \frac{\Delta \kappa}{\alpha} - \Delta \bar{z} \right), \tag{2.13}$$

where $\Delta \ln x \equiv \ln x - \ln x_0$ denotes the log distance to the approximation point for a variable x, $\bar{\eta}_0$ and $\bar{z}$ are weighted averages of the type-specific search effort elasticities and persistent effects, respectively, and the weights reflect the types' contributions to effective search effort. The first-order approximation of the type-specific transition rate is then

$$\Delta \ln \lambda_i = (1 + \eta_i) \frac{\alpha}{1 + \alpha \bar{\eta}_0} \left[\Delta \ln \theta^m + \frac{\Delta \kappa}{\alpha} - \Delta \bar{z} \right] + \Delta z_i. \tag{2.14}$$

Finally, if we were to ignore efficiency differences in search and instead assumed that search is homogeneous across types, we would get a 'reduced form' matching function that relates the average transition rate to labor market tightness

$$\Delta \ln \bar{\lambda} = \frac{\alpha}{1 + \alpha \bar{\eta}_0} \left[(1 + \bar{\eta}_0) \Delta \ln \theta^m + (1 + \bar{\eta}_0) \frac{\Delta \kappa}{\alpha} + (1 - \alpha) \Delta \bar{z} \right]. \tag{2.15}$$

In the appendix we show that for the first-order approximation the aggregate matching elasticity and the search effort elasticities are identified only up to the constraints

$$\frac{\alpha}{1-\alpha}\left(1+\eta_i\right)=\phi_i \text{ for } i\in I, \tag{2.16}$$

where ϕ_i are non-negative constants that are identified. In particular, using the constraint (2.16) the first-order approximation for the observed type-specific employment transition rates can be written as

$$\Delta\ln\lambda_i=\frac{\phi_i}{1+\bar{\phi}_0}\Delta\ln\theta^m+\left[\frac{\phi_i}{1+\bar{\phi}_0}\left(\frac{\Delta\kappa}{\alpha}-\Delta\bar{z}\right)+\Delta z_i\right]. \tag{2.17}$$

Thus, combinations of the aggregate matching elasticity and the search effort elasticities that satisfy the constraints (2.16) generate measures of type-specific persistent effects that are observationally equivalent. In addition, they generate measures of aggregate matching efficiency that are observationally equivalent up to a positive scale factor determined by the matching elasticity. Furthermore, the elasticity of the 'reduced form' aggregate matching function with respect to market tightness can be written as

$$\bar{\alpha}=\frac{\bar{\phi}_0}{1+\bar{\phi}_0}, \tag{2.18}$$

that is, it is independent of the particular choice of matching elasticity and search effort elasticities.

The fact that search effort elasticities are identified only up to the constraints (2.16) means that our estimates of search effort are potentially consistent with either pro-cyclical or counter-cyclical search effort. Equation (2.16) implies that for a sufficiently small (large) matching elasticity all search effort elasticities will be positive (negative). In other words, search effort for all types is pro-cyclical (counter-cyclical) for a sufficiently small (large) matching elasticity.

3. Estimation procedure for matching efficiency and search effort

We now describe our estimation procedure for variable search effort in an environment with heterogeneous search activities. As argued above, given the modeling choice for the search effort motivated by the standard search and matching model, the vacancy elasticity in the matching function, α, and the elasticities of search effort, η_i, are not separately identified. Thus, we propose an estimation procedure for the elasticities of search effort, η_i, conditional on α. In the results section, we then show the estimates of the search effort elasticity for a full range of feasible values of the matching elasticity.

In this version of the paper, we only allow for changes of aggregate matching efficiency, κ, and do not allow for type-specific persistent changes in matching efficiency, that is, $z_i \equiv 0$. We are working on an alternative specification with type-specific persistent changes in matching efficiency.

In a first step towards estimating matching efficiency, we allow for measurement error in type transition rates, i.e.,

$$\ln \lambda_{it}^m = \ln \lambda_{it} + \varepsilon_{it} \text{ with } \varepsilon_{it} \sim N(0, \Sigma), \tag{3.1}$$

and define the measured aggregate search intensity using observations on type-specific transition rates, i.e.,

$$\hat{\lambda}_t^m = \sum_i \lambda_{it}^m u_{it}. \tag{3.2}$$

Combining the definition of type search effort (2.11), aggregate matching rate (2.3), and measured market tightness (3.2), we obtain a log-linear relation between the observed type-specific transition rates and market tightness involving the unknown parameters $(\gamma_i, \eta_i, \alpha)$ and matching efficiency

$$\begin{aligned} (1-\alpha)\ln \lambda_{i,t}^m &= (1-\alpha)\gamma_i + [(1+\eta_i)\alpha]\ln\left(v_t/\hat{\lambda}_t^m\right) \\ &\quad + [(1+\eta_i)\kappa_t + (1-\alpha)(z_{it}+\varepsilon_{it}) + (1+\eta_i)\alpha\mu_t], \end{aligned} \tag{3.3}$$

where μ is a weighted average of the type transition measurement errors.

Equation (3.3) suggests a straightforward two-stage procedure to estimate the search effort elasticities and aggregate matching efficiency. In the first stage, we use OLS to regress measured type transition rates on measured market tightness, and recover estimates of the unknown parameters from the estimated OLS parameters. In the second stage, we treat the error terms from equation (3.3) as generated regressors and estimate matching efficiency using a standard Kalman filter, assuming that matching efficiency follows an AR(1) process

$$\kappa_t = \rho\kappa_{t-1} + \zeta_t \text{ with } \zeta_t \sim N\left(0, \sigma_\zeta^2\right). \tag{3.4}$$

Setting the unconditional expected value of the matching efficiency to zero is a normalization, since the average values of the transition rates are already captured through the type fixed effects. We use maximum likelihood to estimate the parameters of the stochastic process for matching efficiency.

The two-stage procedure is straightforward to implement but faces the same issue as OLS estimates of the matching elasticity: the right hand side variable in equation (3.3) is correlated with the error terms. We therefore use an explicit state-space formulation of the model to obtain a second estimate of search effort elasticities and matching efficiency. For this purpose, expression (3.1) defines the measurement equations and equation (3.4) defines the law of motion for the state. The implicit equation for the aggregate matching rate (2.12) then defines the non-linear mapping from the state to observables. We estimate the state-space model using an extended Kalman filter and we estimate the parameters using maximum likelihood.

Both of our estimation procedures have problems. As we already mentioned the two-stage estimation procedure is potentially biased in the first stage and uses generated regressors in the second stage, and for the extended Kalman filter standard asymptotic properties do not apply for parameter estimates. In order to evaluate the quality of our parameter estimates, we perform Monte Carlo exercises. For each procedure we estimate a VAR for the growth rates of job seekers and vacancies, $z_t = (\ln u_t, \ln v_t)'$, including the estimated series for matching efficiency as an exogenous variable,

$$\Delta z_t = A(L)\,\Delta z_{t-1} + B(L)\,\hat{\kappa}_{t-1} + \varrho_t,$$

where the lag length is determined by the Akaike information criterion. We then simulate the VAR for job seekers and vacancies together with the AR(1) process estimated for matching efficiency, that is, we treat matching efficiency as exogenous. For the artificial sample of job seekers, vacancies, and matching efficiency we then use equations (2.11), (2.12), and (3.1) to generate the associated sample of transition rates, and estimate the parameters using either procedure.

Finally, as noted above, our estimates of search effort elasticities and matching efficiency are conditional on the matching function elasticity α. We have shown above that to a first order approximation the matching elasticity and the search effort elasticities are not separately identified. This also applies for our two estimation procedures which do not impose a global linear approximation. For the two-stage procedure, it follows from equation (3.3) that a maximum likelihood procedure will set the matching elasticity to one, $\alpha = 1$. To see this suppose we have an estimate for the unknown parameters $(\gamma_i, \eta_i, \alpha)$. We can then scale the matching elasticity α and appropriately rescale the other parameters such that none of the estimated error terms are affected, except for the estimated matching efficiency. Furthermore, we can drive the value of the matching efficiency to zero for a large enough scale factor. Only the restriction that the matching elasticity is bounded between zero and one prevents us from doing that and we end up with an estimated matching elasticity of one. For our second procedure it turns out that the likelihood function is essentially flat for the matching elasticity, even though the extended Kalman filter does not use a global linear approximation.

4. Estimating matching efficiency and search effort

This section estimates the responsiveness of search effort to the aggregate matching rate and the implied matching efficiency allowing for heterogeneity in search effort.

4.1. Data

We consider two alternative classifications of the non-employed job seekers. The first classification consists of three groups of unemployed job seekers ranked by duration of unemployment: less than 5 weeks, between 5 and 26 weeks, and more than 26 weeks of reported unemployment, respectively. The second classification consists of four groups of non-employed job seekers characterized by their labor market status (unemployed or out of the labor force) and gender (male or female).

The method for the estimation of the responsiveness of search effort to the aggregate matching rate and the implied matching efficiency proposed in this paper requires the following data series: the job finding rate of different groups of job seekers, the number of job seekers in each group, and aggregate vacancies.

The aggregate vacancy series are from the Job Openings and Labor Turnover Survey (JOLTS) program of the BLS for the period January 2001 to December 2013.[8] We construct the job finding probabilities of different groups of non-employed job seekers using the micro data from the Current Population Survey (CPS) basic monthly files. We follow Madrian and Lefgren (1999) and Shimer (2012) and match individuals from month to month using information on race, age and sex besides individual and household's identification number. In the analysis, we weigh each individual by the average of the individual's CPS sampling weights from adjacent months.[9] The transition probability of a group is the fraction of individuals that transition between labor market states in two adjacent months.[10] We transform the month-to-month transition probabilities to continuous time transition rates using two procedures. For the sample with unemployment duration contingent transitions we use the exit probabilities to employment and OLF, and assume that exits do not return to unemployment in the same month. This defines the following relation between the discrete time

[8]The JOLTS vacancy series are available only since January 2001 and effectively limits the sample we consider, We have not yet pursued the possibility to use the Conference Board series for help wanted ads to extend the sample to years before 2001, for example Barnichon (2010).

[9]All series are seasonally adjusted using Watson (1996) implementation of the X-11 procedure.

[10]In the analysis, we follow the BLS approach and treat the reported labor force status as a true status. Frazis, Robinson, Evans, and Duff (2005) describes that the main reason for why the BLS does not correct responses for a potential error is a lack of methodology or the data that would guide the correction.

transition probabilities p and the continuous time rates λ,

$$\begin{aligned} p_{UE} &= \frac{\lambda_{UE}}{\lambda_{UE}+\lambda_{UI}}\left[1-e^{-(\lambda_{UE}+\lambda_{UI})}\right] \\ p_{UI} &= \frac{\lambda_{UI}}{\lambda_{UE}+\lambda_{UI}}\left[1-e^{-(\lambda_{UE}+\lambda_{UI})}\right] \end{aligned}$$

For the sample with labor-market state and gender contingent transitions, we use the procedure in Shimer (2012) to recover the continuous time transition rates to employment from the complete matrix of transition probabilities between all labor market states.

4.2. Duration-contingent search effort

4.2.1. Search effort elasticities

- Table 1, columns (1.a) and (2.a) show parameter estimates - the search effort elasticities and the matching efficiency from our two procedures - contingent on matching elasticity, $\alpha = 0.5$. Panel A shows the estimates for the elasticity of search effort with respect to the aggregate matching rate. Both estimation procedures yield comparable estimates for the search effort elasticity. Given $\alpha = 0.5$, search effort is counter-cyclical for all three duration-contingent groups of the unemployed: as the aggregate matching rate declines and unemployment increases, search effort goes up, but effective job finding rates remain positively correlated with the aggregate matching rate. Across durations, short-duration unemployment is more sensitive to the aggregate matching rate than the long-duration unemployment. The asymptotic standard errors of the parameter estimates suggest that the differences in search effort elasticity are significant. Comparing the estimates for search effort elasticity with the results from the Monte Carlo exercise (Table 1, columns (1.b) and (2.b)) it appears that there is no substantial bias in the OLS procedure, and that the differences in effort elasticity are indeed significant.

- Figure 2: search effort elasticities for the three groups of the unemployed as a function of matching elasticity:

  - pro-(counter-)cyclical search effort for low, $\alpha < 0.3$, (high, $\alpha > 0.4$) matching elasticity.

[Table 1. Search effort contingent on duration of unemployment]

[Figure 2. Search effort elasticities for duration-contingent employment transition rates]

4.2.2. Aggregate matching efficiency

- Both procedures estimate matching efficiency as a highly persistent process (Table 1, Panel B). Based on the Monte Carlo experiment the two stage OLS procedure does not yield precise estimates of the persistence.

- The left panel of Figure 3 shows the cumulative changes in the aggregate matching rate, $\ln \lambda$, and the contributions coming from the changes in the measured market tightness, $\alpha \ln \theta^m$, the aggregate quality adjustment, $-\alpha \ln \bar{\rho}$, and the aggregate matching efficiency, κ, contingent on the matching elasticity:

  - For most values of the matching elasticity ($\alpha = 0.2$ or $\alpha = 0.5$) we see a large impact of measured market tightness and a limited impact of quality adjustment,
  - but once the matching elasticity becomes large ($\alpha = 0.8$) , but get the reverse.

- The right panel of Figure 3 shows the estimated search effort for the three groups of the unemployed, contingent on the matching elasticity:

  - For low matching elasticity ($\alpha = 0.2$) search effort is pro-cyclical and the impact of average quality adjustment on the aggregate matching rate is pro-cyclical.
  - The reverse is true for a higher matching elasticity ($\alpha = 0.5$ and $\alpha = 0.8$).

- Figure 4: matching efficiency contingent on matching elasticity

  - Common for all matching elasticities is the cyclical pattern and a declining trend for the post-2007 years,
  - The volatility of matching efficiency increases with matching elasticity,
  - Not accounting for heterogeneity of search effort (i.e., estimating $\overline{\kappa}$ using equation (2.8)) yields a measure of matching efficiency that shows a steeper decline after 2007, and that is more volatile after 2007.
    - The 'reduced form' matching elasticity implied by the estimated transition rates is $\bar{\alpha} = 0.34$.

[Figure 3. Aggregate matching function and search effort for duration-contingent transition rates]

[Figure 4. Matching efficiency for duration-contingent employment transition rates]

4.3. Gender and LFS-contingent search effort

4.3.1. Search effort elasticities

- Table 2, columns (1.a) and (2.a) show parameter estimates contingent on matching elasticity, $\alpha = 0.5$. Both estimation procedures suggest that the search effort of those OLF is more sensitive to changes in the aggregate matching rate than is the search effort of the unemployed. The procedures yield comparable estimates for the search effort elasticity for those OLF, but they differ in their assessment of the cyclicality of search effort of the unemployed. The two-stage OLS procedure suggests pro-cyclical search effort, whereas the Kalman filter suggests counter-cyclical search effort. But note that the estimated search effort elasticities from both procedures are close to zero for the unemployed. Comparing the estimates for search effort elasticity with the results from the Monte Carlo exercise (Table 2, columns (1.b) and (2.b)) it appears that there is no substantial bias for the Kalman filter, but that the two-stage OLS procedure is biased towards finding lower elasticities, especially for the unemployed, and that the asymptotic standard errors understate the true parameter uncertainty.

- Figure 5: search effort elasticities contingent on LFS and gender as a function of matching elasticity

  - pro-(counter-)cyclical search effort if matching elasticity is below (above) the critical value α^*
  - The critical value for unemployed is $\alpha^* = 0.5$, and the critical value for OLF is $\alpha^* = 0.25$.
  - That the estimated search effort elasticity is not significantly different from zero in Table 2 seems to be related to the fact that we are estimating it at the critical value for the matching elasticity.

[Table 2. Search effort contingent on labor market status]

[Figure 5. Search effort elasticities for LFS-contingent employment transition rates]

4.3.2. Aggregate matching efficiency

- Table 2, Panel B: The two-stage OLS procedure yields a substantial lower estimate of the persistence of matching efficiency than does the extended Kalman filter. Based on the Monte Carlo experiment estimates of the persistence from the two stage OLS procedure are not biased, but they are also much more imprecise than suggested by the asymptotic errors.

- The left panel of Figure 6 shows the cumulative changes in the aggregate matching rate, $\ln \lambda$, and the contributions coming from the changes in the measured market tightness, $\alpha \ln \theta^m$, the aggregate quality adjustment, $-\alpha \ln \bar{\rho}$, and the aggregate matching efficiency, κ, contingent on the matching elasticity.
  - For low values of the matching elasticity ($\alpha = 0.2$) we see a large impact of measured market tightness and a limited impact of quality adjustment,
  - but as the matching elasticity becomes large ($\alpha = 0.5$ and $\alpha = 0.8$) we get the reverse.
  - This is the same pattern as for the decomposition based on unemployment duration.
- The right panel of Figure 6 shows the estimated search effort for the four groups of non-employed, contingent on the matching elasticity:
  - For a low matching elasticity ($\alpha = 0.2$) search effort is pro-cyclical and the impact of average quality adjustment on the aggregate matching rate is pro-cyclical.
  - The reverse is true for a higher matching elasticity ($\alpha = 0.5$ and $\alpha = 0.8$).
- Figure 7: matching efficiency contingent on matching elasticity
  - Common for all matching elasticities is the cyclical pattern and a declining trend for the post-2007 years,
  - The volatility of matching efficiency increases with matching elasticity,
  - Not accounting for heterogeneity of search effort (i.e., estimating $\overline{\kappa}$ using equation (2.8)) yields a measure of matching efficiency that is very different for the post-2007 period: it suggests a temporary increase of aggregate matching efficiency in the years 2008 and 2009 before it returns to its negative trend.
    * The 'reduced form' matching elasticity implied by the estimated transition rates is $\bar{\alpha} = 0.36$.

[Figure 6. Aggregate matching function and search effort for LFS-contingent transition rates]

[Figure 7. Matching efficiency for LFS-contingent employment transition rates]

5. Conclusion

References

[1] Barnichon, Regis. 2010. Building a composite help-wanted index. Economics Letters 109, 175-178.

[2] Barnichon, Regis, and Andrew Figura. 2011. What Drives Movements in the Unemployment Rate? A Decomposition of the Beveridge Curve. mimeo.

[3] Baxter, Marianne, and Robert G. King. 1999. Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series. Review Of Economics And Statistics 81, no. 4: 575-593.

[4] Costain and Reiter. 2008.

[5] Davis, Steven J. Comment on "Job Search, Emotional Well-Being, and Job Finding in a Period of Mass Unemployment," by Alan Krueger and Andreas Mueller, Brookings Papers on Economic Activity (2011), 58–81.

[6] Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2013. The Establishment-Level Behavior of Vacancies and Hiring. Quarterly Journal of Economics 128 (2): 581-622.

[7] Elsby, Michael W.I., Ryan Michaels, and David Ratner. Forthcoming. The Beveridge Curve: A Survey. Journal of Economic Literature. Downloaded from `https://sites.google.com/site/mikeelsby/` on 2/26/2014.

[8] Faberman, Jason R., and Marianna Kudlyak. 2014. The Intensity of Job Search and Search Duration. Richmond FED WP No. 14-12.

[9] Frazis, Harley J., Edwin L. Robinson, Thomas D. Evans, and Martha A. Duff. 2005. Estimating Gross Flows Consistent with Stocks in the CPS. Monthly Labor Review, Vol. 128 (9): 3-9.

[10] Gomme, Paul, and Damba Lkhagvasuren. Forthcoming. Worker Search Effort as an Amplification Mechanism. Journal of Monetray Economics. Accessed at https://sites.google.com/site/dlkhagva/research.

[11] Hall, Robert E., and Sam Schulhofer-Wohl. 2015. Measuring Matching Efficiency with Heterogeneous Jobseekers. NBER Working Paper No. 20939.

[12] Kroft, Kory, Fabian Lange, Matthew J. Notowidigdo, and Lawrence Katz. 2013. Long-Term Unemployment and the Great Recession: The Role of Composition, Duration Dependence, and Non-Participation. Mimeo September 2013. Downloaded from http://korykroft.com/wordpress/KLNK_LTU_and_Great_Recession_sep16_2013.pdf.

[13] Krueger, Alan, and Andreas Mueller. 2011. Job Search, Emotional Well-Being, and Job Finding in a Period of Mass Unemployment, Brookings Papers on Economic Activity, Vol. 42(1): 1-81.

[14] Madrian, Brigitte C., and Lars John Lefgren. 1999. A Note on Longitudinally Matching Current Population Survey (CPS) Respondents. NBER Working Paper No. t0247..

[15] Mukoyama, Toshihiko, Christina Patterson, and Aysegul Sahin. 2013. Job Search Behavior over the Business Cycle. 2013 Meeting Papers 988, Society for Economic Dynamics.

[16] Petrongolo, Barbara, and Christopher A. Pissarides. 2001. Looking into the Black Box: A Survey of the Matching Function. Journal of Economic Literature 39, 390-431.

[17] Pissarides, Christopher A.. 2000. Equilibrium Unemployment Theory. The MIT Press.

[18] Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Givanni L. Violante. 2014. Mismatch Unemployment. American Economic Review, Vol. 104(11): 3529-64.

[19] Sedlacek, Petr. 2014. The Aggregate Matching Function and Job Search from Outside Unemployment. Mimeo. Downloaded from http://www.wiwi.uni-bonn.de/sedlacek/Documents/Working/MatchingNUS_20140424.pdf.

[20] Shimer, Robert. 2004. Search Intensity. Mimeo, downloadable from https://sites.google.com/site/robertshimer/research/workingpapers.

[21] Shimer, Robert. 2012. Reassessing the Ins and Outs of Unemployment. Review of Economic Dynamics 15, 127-148.

[22] Veracierto, Marcelo. 2011. Worker Flows and Matching Efficiency. Federal Reserve Bank of Chicago Economic Perspectives v.35 4th Quarter, 147-169.

[23] Watson, Mark M. 1996. Comment on "Is Seasonal Adjustment a Linear or Nonlinear Data Filtering Process," Journal of Business and Economic Statistics, Vol. 14, No. 3.

6. Appendix. Log linear approximation

- Aggregate matching elasticity and type search effort elasticities are not separately identified
- Aggregate matching efficiency is identified up to a scalar transformation
- The matching elasticity of a reduced form aggregate matching function that ignores heterogeneity is identified

A first order log-linear approximation of the expression for the average search effort, (2.5), as a function of the aggregate matching rate yields

$$\begin{aligned}
\ln \bar{\rho} - \ln \bar{\rho}_0 &= \frac{1}{\bar{\rho}_0}\left[\sum_i \eta_i \frac{u_{i,0}}{u_0} e^{\gamma_i + z_{i0} + \eta_i \ln \lambda_0}\right](\ln \lambda - \ln \lambda_0) + \frac{1}{\bar{\rho}_0}\left[\sum_i \frac{u_{i,0}}{u_0} e^{\gamma_i + z_{i0} + \eta_i \ln \lambda_0}(z_i - z_{i0})\right] \\
\Delta \ln \bar{\rho} &= \left[\sum_i \eta_i \frac{(u_{i,0}/u_0)\, e^{\gamma_i + z_{i0} + \eta_i \ln \lambda_0}}{\bar{\rho}_0}\right]\Delta \ln \lambda + \sum_i \frac{\frac{u_{i,0}}{u_0} e^{\gamma_i + z_{i0} + \eta_i \ln \lambda_0}}{\bar{\rho}_0}\Delta z_i
\end{aligned}$$

where $\Delta \ln x \equiv \ln x - \ln x_0$. Define the average search effort elasticity $\bar{\eta}_0$ and the average type-specific effect $\Delta \bar{z}$

$$\begin{aligned}
\bar{\eta}_0 &= \sum_i \eta_i \omega_{i,0} \text{ and } \Delta \bar{z} = \sum_i \omega_{i,0} \Delta z_i \\
\text{with } \omega_{i,0} &= \frac{(u_{i,0}/u_0)\, e^{\gamma_i + z_{i0} + \eta_i \ln \lambda_0}}{\bar{\rho}_0} \text{ and } \sum_i \omega_{i,0} = 1.
\end{aligned}$$

and we get

$$\Delta \ln \bar{\rho} = \bar{\eta}_0 \Delta \lambda + \Delta \bar{z}. \tag{6.1}$$

Then a first order approximation of the expression for the aggregate matching rate (2.12) is

$$\begin{aligned}
\Delta \ln \lambda &= \Delta \kappa + \alpha (\Delta \ln \theta^m - \Delta \ln \bar{\rho}) \\
&= \Delta \kappa + \alpha \Delta \ln \theta^m - \alpha \bar{\eta}_0 \Delta \ln \lambda - \alpha \Delta \bar{z}
\end{aligned}$$

and we can solve for the aggregate matching rate as

$$\Delta \ln \lambda = (1 + \alpha \bar{\eta}_0)^{-1} (\Delta \kappa - \alpha \Delta \bar{z} + \alpha \Delta \ln \theta^m) \tag{6.2}$$

We can also write the average transition rate across types as

$$\bar{\lambda} = \sum_i \frac{u_i}{u} \lambda_i = \sum_i \frac{u_i}{u} e^{\gamma_i + z_i + (1+\eta_i) \ln \lambda}$$

and the first order log linear approximation is

$$\Delta \ln \bar{\lambda} = \left[\sum_i (1+\eta_i) \frac{(u_{i,0}/u_0)\, e^{\gamma_i + z_{i0} + (1+\eta_i)\ln \lambda_0}}{\bar{\lambda}_0} \right] \Delta \ln \lambda + \sum_i \frac{(u_{i,0}/u_0)\, e^{\gamma_i + z_{i0} + (1+\eta_i)\ln \lambda_0}}{\bar{\lambda}_0} \Delta z_i$$

Note that

$$\frac{(u_{i,0}/u_0)\, e^{\gamma_i + z_{i0} + (1+\eta_{i0})\ln \lambda_0}}{\bar{\lambda}_0} = \frac{\lambda_0 \,(u_{i,0}/u_0)\, e^{\gamma_i + z_{i0} + \eta_i \ln \lambda_0}}{\lambda_0 \sum_j \frac{u_{j,0}}{u_0} e^{c_j + z_{i0} + \eta_j \ln \lambda_0}} = \omega_{i,0}.$$

Thus the first order approximation for the average exit rate simplifies to

$$\Delta \ln \bar{\lambda} = \left[\sum_i (1+\eta_i)\, \omega_{i,0} \right] \Delta \ln \lambda + \Delta \bar{z} = (1+\bar{\eta}_0)\, \Delta \ln \lambda + \Delta \bar{z}$$

Using the expression for the aggregate matching rate we obtain the following relation between the average employment transition rate and the standard measure of market tightness

$$\Delta \ln \bar{\lambda} = (1+\bar{\eta}_0) \frac{\Delta\kappa - \alpha \Delta \bar{z} + \alpha \Delta \ln \theta^m}{1+\alpha \bar{\eta}_0} + \Delta \bar{z}$$

we get the 'reduced form' matching function that assumes homogeneity in search effort

$$\Delta \ln \bar{\lambda} = (1+\alpha\bar{\eta}_0)^{-1} \left[(\alpha + \alpha\bar{\eta}_0)\, \Delta \ln \theta^m + (1+\bar{\eta}_0)\, \Delta\kappa + (1-\alpha)\, \Delta \bar{z} \right] \tag{6.3}$$

and the matching function elasticity from aggregate data is

$$\bar{\alpha} = \frac{\alpha\,(1+\bar{\eta}_0)}{1+\alpha\bar{\eta}_0} \tag{6.4}$$

This expression is analogous to the single type relation with the weighted average of search effort elasticities replacing the single type search effort elasticity.

6.0.3. Lack of identification for search effort

We now show that up to a first order approximation the search effort elasticities and the matching elasticity are not separately identified. Suppose you are given a parameterization of the model with search effort elasticities by type and the matching elasticity, $(\hat{\alpha}, \hat{\eta}_i)$, and consider alternative parameterizations that satisfy the constraints

$$\frac{\alpha}{1-\alpha}(1+\eta_i) = \phi_i = \frac{\hat{\alpha}}{1-\hat{\alpha}}(1+\hat{\eta}_i) \tag{6.5}$$

Substituting this expression in the definition for the average search effort elasticity we get

$$1+\bar{\eta}_0=\sum_i(1+\eta_i)\,\omega_{i,0}=\sum_i\omega_{i,0}\phi_i\frac{1-\alpha}{\alpha}=\frac{1-\alpha}{\alpha}\sum_i\omega_{i,0}\phi_i=\frac{1-\alpha}{\alpha}\bar{\phi}_0.$$

We can now define the log-linear approximation of the employment transition rates for types

$$\begin{aligned}\Delta\ln\lambda_i &= \Delta z_i+(1+\eta_i)\,\Delta\ln\lambda\\ &= \Delta z_i+\frac{1+\eta_i}{1+\alpha\bar{\eta}_0}\left(\Delta\kappa-\alpha\Delta\bar{z}+\alpha\Delta\ln\theta^m\right)\end{aligned}$$

or

$$\Delta\ln\lambda_i=\frac{\alpha\,(1+\eta_i)}{1+\alpha\bar{\eta}_0}\left[\Delta\ln\theta^m-\Delta\bar{z}+\frac{\Delta\kappa}{\alpha}\right]+\Delta z_i \tag{6.6}$$

We can rewrite the coefficient on measured tightness as

$$\begin{aligned}\alpha\frac{1+\eta_i}{1+\alpha\bar{\eta}_0} &= (1-\alpha)\,\phi_i\left[1+\alpha\left(\frac{1-\alpha}{\alpha}\bar{\phi}_0-1\right)\right]^{-1}\\ &= (1-\alpha)\,\phi_i\left[1+(1-\alpha)\,\bar{\phi}_0-\alpha\right]^{-1}\\ &= (1-\alpha)\,\phi_i\left[1+(1-\alpha)\sum_i\omega_i\phi_i-\alpha\right]^{-1}\\ &= \frac{\phi_i}{1+\bar{\phi}_0}\end{aligned}$$

Thus the first order approximation for the employment transition rates of types becomes

$$\Delta\ln\lambda_i=\frac{\phi_i}{1+\bar{\phi}_0}\Delta\ln\theta^m+\left[\frac{\phi_i}{1+\bar{\phi}_0}\left(\frac{\Delta\kappa}{\alpha}-\Delta\bar{z}\right)+\Delta z_i\right]$$

This means that in a first order approximation search effort elasticities for types and matching elasticity are identified only up to the constraints imposed by (2.16). Furthermore, aggregate matching efficiency is identified only up to a scale factor determined by the matching elasticity, but persistent changes in type-specific matching efficiency are identified.

6.0.4. Identification of reduced form matching elasticity

Another implication of constrained identification (2.16) is that the reduced form matching elasticity from aggregate data relating the average matching rate to labor market tightness, (6.4), is independent of α.

$$\bar{\alpha} = \frac{(1-\alpha)\,\bar{\phi}_0}{1+\left[(1-\alpha)\,\bar{\phi}_0-\alpha\right]} = \frac{\bar{\phi}_0}{1+\bar{\phi}_0} \tag{6.7}$$

7. Tables

Table 1. Search effort contingent on duration of unemployment

	Two Stage Estimation		Extended Kalman Filter	
	(1.a)	(1.b)	(2.a)	(2.b)
	A. Search Effort Elasticity η_i			
1-4 weeks :	-0.6382	-0.6793	-0.6146	-0.6288
	(0.0444)	(0.0576)	(0.0464)	(0.0245)
5-26 weeks :	-0.3970	-0.4392	-0.4293	-0.4449
	(0.0530)	(0.0793)	(0.0731)	(0.0331)
>26 weeks :	-0.3023	-0.3430	-0.2880	-0.3040
	(0.0783)	(0.0894)	(0.1216)	(0.0464)
	B. Matching Efficiency κ			
ρ	0.9950	0.4622	0.9988	0.9706
	(0.0069)	(0.5615)	(0.0014)	(0.0477)
σ_ζ	0.0111	0.0525	0.0094	0.0039
	(0.0034)	(0.0480)	(0.0024)	(0.0006)
	C. Standard Deviations of Measurement Errors ϵ_i			
1-4 weeks :	0.1059	0.1293	0.0422	0.0202
	(0.0061)	(0.0173)	(0.0025)	(0.0026)
5-26 weeks :	0.1130	0.1442	0.0213	0.0052
	(0.0067)	(0.0587)	(0.0012)	(0.0009)
>26 weeks :	0.1536	0.1819	0.0194	0.0013
	(0.0094)	(0.1310)	(0.0018)	(0.0005)

Note: Columns (a) display parameter estimates and their asymptotic standard errors in parentheses, and columns (b) display the mean and standard deviation from 1,000 Monte Carlo replications

Table 2. Search effort contingent on labor market status

	Two Stage Estimation		Extended Kalman Filter	
	(1.a)	(1.b)	(2.a)	(2.b)
		A. Search Effort Elasticity η_i		
Men U	0.0574	-0.2191	-0.1422	-0.1154
	(0.0817)	(0.2250)	(0.0309)	(0.0415)
Women U	0.0686	-0.2385	-0.1012	-0.0726
	(0.0936)	(0.2492)	(0.0681)	(0.0467)
Men, OLF	-0.6207	-0.7392	-0.6712	-0.6600
	(0.0448)	(0.0984)	(0.0133)	(0.0189)
Women, OLF	-0.6621	-0.7991	-0.6983	-0.6883
	(0.0427)	(0.1111)	(0.0086)	(0.0172)
		B. Matching Efficiency κ		
ρ	0.5571	0.5288	0.9993	0.9679
	(0.0000)	(0.1141)	(0.0010)	(0.0338)
σ_ζ	0.0662	0.0394	0.0059	0.0009
	(0.0000)	(0.0383)	(0.0004)	(0.0008)
	C. Standard Deviations of Measurement Errors ϵ_i			
Men, U :	0.0396	0.0394	0.0268	0.0313
	(0.0000)	(0.0383)	(0.0017)	(0.0290)
Women, U :	0.0807	0.0966	0.0281	0.0321
	(0.0000)	(0.0240)	(0.0015)	(0.0314)
Men, I :	0.0642	0.0693	0.0023	0.0004
	(0.0000)	(0.0074)	(0.0001)	(0.0004)
Women, I :	0.0659	0.0682	0.0012	0.0002
	(0.0000)	(0.0118)	(0.0001)	(0.0004)

Notes: See Table 1.

8. Figures

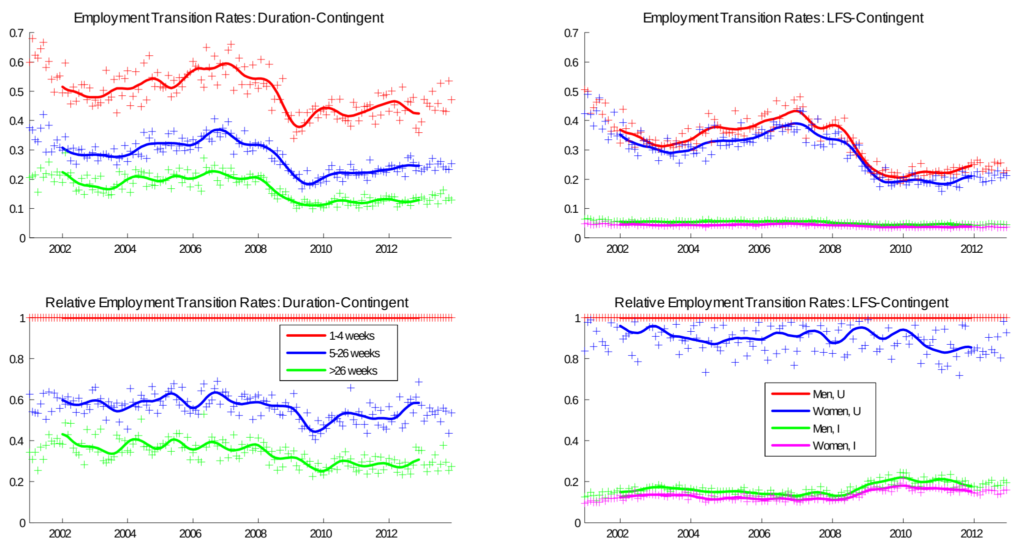

Figure 1. Transition Rates to Employment

Note: The two left-hand side panels display transition rates to employment contingent on the reported unemployment duration: less than 5 weeks, 5 to 26 weeks, and more than 26 weeks. The two right-hand side panels display transition rates contingent on the labor force status (unemployed or OLF) and gender. Crosses indicate the observed transition rates and lines are smoothed transition rates after applying a Baxter and King (1999) band pass filter that removes frequencies with periodicity of less than 12 months. The two top panels display the transition rates, and the two bottom panels display transition rates relative to the group with the highest transition rate: 'less than 5 weeks' for duration-contingent and 'male unemployed' for LFS-contingent.

8.1. Duration-contingent transition rates

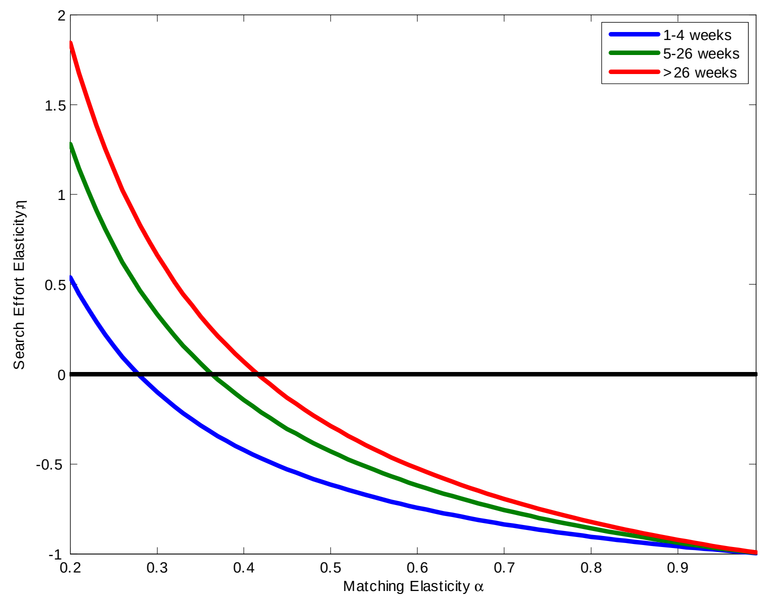

Figure 2. Search effort elasticities for duration-contingent employment transition rates

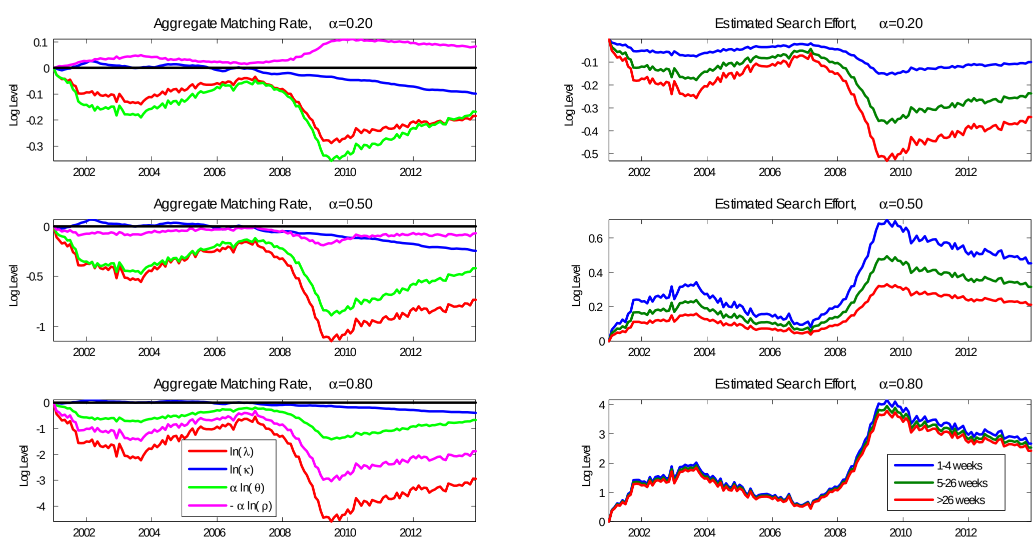

Figure 3. Aggregate matching function and search effort for duration-contingent transition rates

Note: The rows display the estimated aggregate transition rate and its determinants and search effort for different values of the matching elasticity, $\alpha \in \{0.2, 0.5, 0.8\}$. The left-hand side panels display the log levels of the transition rate and its components: measured market tightness, average quality, and matching efficiency. The right-hand side panels display the log-level of duration contingent search effort. All log-levels are normalized to zero in January

2001.

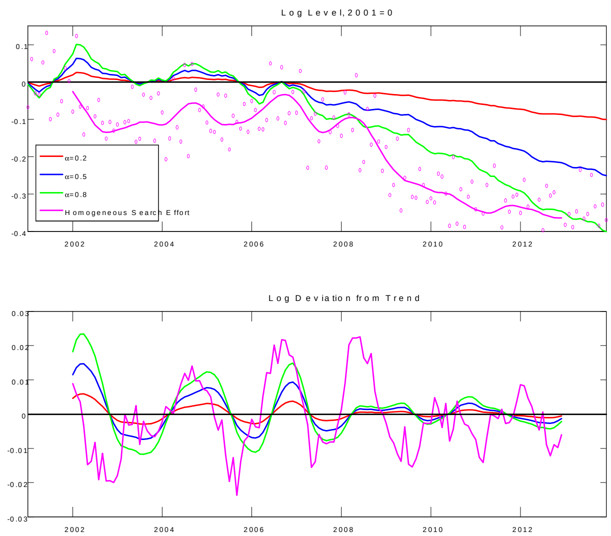

Figure 4. Matching efficiency for duration-contingent employment transition rates

Note: The top panel displays estimated matching elasticity for three different values of the matching elasticity, $\alpha \in \{0.2, 0.5, 0.8\}$, and for a 'reduced form' approach that assumes homogeneous search efficiency with a matching elasticity $\bar{\alpha} = 0.34$ implied by the estimated search effort elasticities. For the 'reduced form' we smooth the raw data (circles) by applying a Baxter and King (1999) band pass filter that removes movements with periodicity of less than 12 months. The bottom panel displays the cyclical fluctuations of matching efficiency obtained by applying a band pass filet that removes movements with periodicity between 2 and 10 years.

8.2. LFS-contingent transition rates

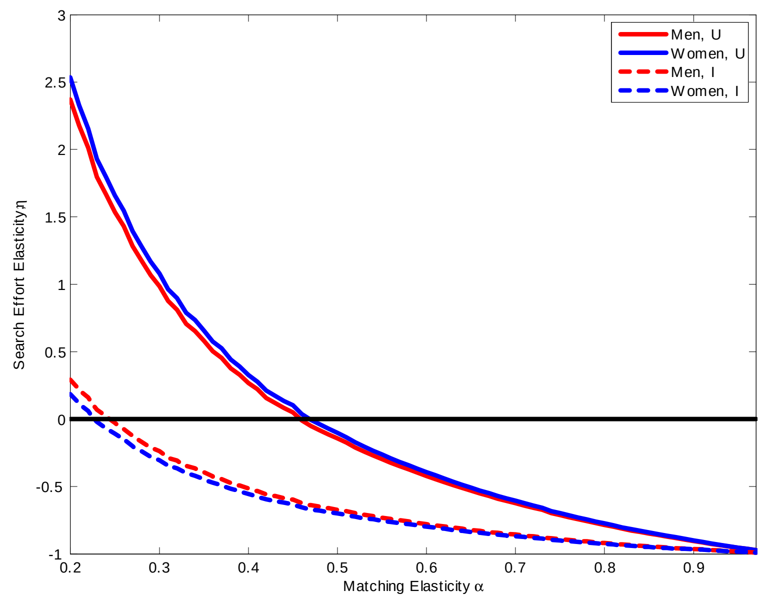

Figure 5. Search effort elasticities for LFS-contingent employment transition rates

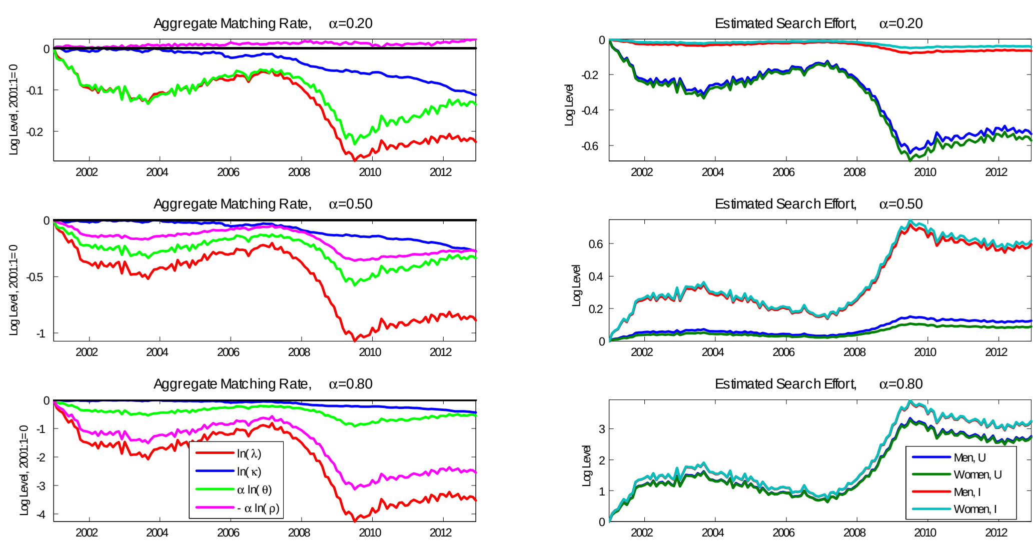

Figure 6. Aggregate matching function and search effort for LFS-contingent transition rates

Note: The rows display the estimated aggregate transition rate and its determinants and search effort for different values of the matching elasticity, $\alpha \in \{0.2, 0.5, 0.8\}$. The left-hand side panels display the log levels of the transition rate and its components: measured market tightness, average quality, and matching efficiency. The right-hand side panels display the log-level of LFS and gender contingent search effort. All log-levels are normalized to zero in January 2001.

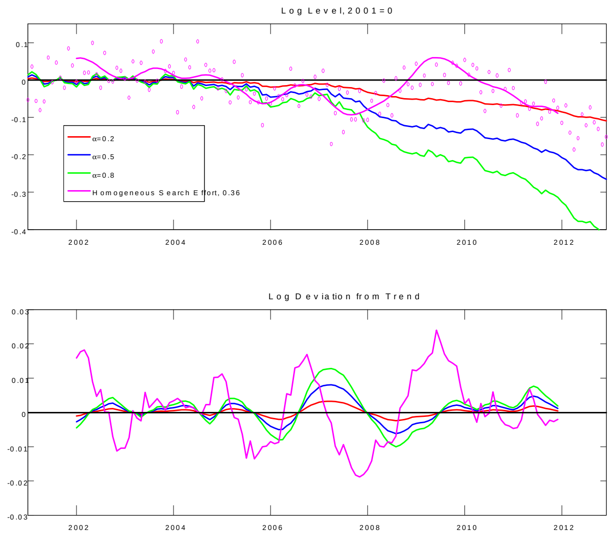

Figure 7. Matching efficiency for LFS-contingent employment transition rates

Note: The top panel displays estimated matching elasticity for three different values of the matching elasticity, $\alpha \in \{0.2, 0.5, 0.8\}$, and for a 'reduced form' approach that assumes homogeneous search efficiency with a matching elasticity $\bar{\alpha} = 0.36$ implied by the estimated search effort elasticities. For the 'reduced form' we smooth the raw data (circles) by applying a Baxter and King (1999) band pass filter that removes frequencies with periodicity of less than 12 months. The bottom panel displays the cyclical fluctuations of matching efficiency obtained by applying a band pass filet that removes movements with periodicity between 2 and 10 years.