What drives movements in the unemployment rate?*

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Abstract

We use a Beveridge curve framework and micro data to decompose unemployment rate movements into: (1) a component driven by changes in labor demand (2) a component driven by changes in labor supply and (3) a component driven by changes in the efficiency of matching unemployed workers to jobs. We find that, historically, cyclical movements in unemployment are dominated by changes in labor demand, although changes in the efficiency of matching can also plays a role. Secular changes in unemployment are dominated by changes in labor supply. The most recent labor market downturn appears to be adhering to the historical pattern: Changes in labor demand appear to explain the large majority of the increase in unemployment since 2007, though decreases in matching efficiency have been particularly important.

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1 Introduction

The unemployment rate is an important indicator of economic activity. Understanding its movements is useful in assessing the causes of economic fluctuations and their impact on welfare, as well as assessing inflationary pressures in the economy. To help understand the forces driving fluctuations in the unemployment rate, we use a Beveridge curve framework and micro data to decompose unemployment rate movements into: (1) a component driven by changes in labor demand (2) a component driven by changes in labor supply and (3) a component driven by changes in the efficiency of matching unemployed workers to jobs.

We find that, historically, cyclical movements in unemployment are dominated by changes in labor demand, although changes in the efficiency of matching also play a role. Secular changes in unemployment are dominated by changes in labor supply. The most recent labor market downturn appears to be adhering to the historical pattern: Changes in labor demand appear to explain the large majority of the increase in unemployment since 2007, though decreases in matching efficiency have been particularly important.

We accomplish our decomposition by first decomposing unemployment rate movements into a component responding to changes in unemployment inflows and a component responding to changes in unemployment outflows, as in Fujita and Ramey (2009) and Elsby, Michaels and Solon (2009). Then we decompose the outflow component into a component driven by changes in labor demand and a component driven by changes in the efficiency of matching workers to jobs. To do this, we estimate an aggregate matching function tying levels of vacancies and unemployment to transitions from unemployment into employment. The demand driven component can be represented as movements along a stable Beveridge curve, while the match efficiency component can be represented as a shift in the Beveridge curve.

We introduce our approach with a simple framework that sidesteps workers heterogeneity and movements in and out of the labor force, but we successively relax these two assumptions.

First, because changes in the composition of the unemployment pool could affect our matching function estimates, we use micro data to control for individual characteristics and better understand the nature of the changes in matching efficiency. Using average transition rates could hide some shifts in the underlying characteristics of the unemployed that may lead to changes in matching efficiency. We find that shifts in the composition of the unemployment pool are indeed important, accounting for most of the shifts in the matching function until 2006 and half of the apparent decline in matching efficiency in the 2008-2009 recession. This composition effect is mostly due to two factors: (i) a higher concentration of unemployed workers in states with distressed labor markets and lower than average job finding rate, and (ii) a larger fraction of unemployed workers on permanent layoffs.

Second, because changes in unemployment inflows (and shifts in the Beveridge curve) could be caused by changes in labor demand as well as changes in demographics or labor supply, we generalize our decomposition by distinguishing layoffs from quits and by allowing for movements in and out of the labor force. That way, we can decompose unemployment fluctuations into a labor demand component and a labor supply component. We identify the labor demand component from movements along the Beveridge curve and from shifts in the Beveridge curve due to layoffs. We identify the labor supply component from quits and movements in and out of the labor force. We find that labor demand and labor supply contribute approximately equally to unemployment's variance. However, these two forces play very different roles at different frequencies. At business cycle frequencies, labor demand accounts for two thirds of unemployment's variance. In contrast, at low frequencies, most of unemployment movements are caused by changes in labor supply, in particular the aging of the baby boom, the increase in women's labor force participation and the increasing attachment of women to the labor force.

Our paper is related to two strands in the literature. The first strand investigates the relative responsibility of unemployment inflows and outflows in accounting for changes in unemployment. We take this literature one step further by decomposing inflows and outflows into economically meaningful components that allow us to say something about the economic forces driving movements in unemployment. Our use of an aggregate matching function and the Beveridge curve to accomplish this decomposition harks back to an earlier strand in the literature (e.g. Lipsey, 1965, Abraham, 1987, Blanchard and Diamond, 1989) that relied on the Beveridge curve to distinguish between changes in labor demand (movements along the Beveridge curve) and shifts in sectoral reallocation (shifts in the Beveridge curve). We build on this literature by using unemployment inflows and outflows and an aggregate matching function to better identify causes of Beveridge curve shifts. Further, we use micro data to better distinguish between movements along the Beveridge curve and shifts in the Beveridge curve due to a changing composition of unemployment, as well as to separate Beveridge curve shifts due to changing inflows into a component likely driven by labor demand and a component driven by long-term demographic and behavioral changes.

The next section lays the theoretical groundwork for our decomposition. Section 3 estimates an aggregate matching function, which we use to decompose unemployment outflows into movements along the Beveridge curve due to changes in labor demand, shifts in the Beveridge curve, and changes in the matching function. Section 4 uses micro data to provide a more precise distinction between shifts in and movements along the Beveridge curve, as well as to trace some of the shifts in the Beveridge curve to changes in the composition of the labor force. Section 5 extends the Beveridge curve framework to include flows to and from out of the labor force, which is particularly important in explaining long-term changes in the unemployment rate. Section 6 concludes.

2 A basic Beveridge curve decomposition

In this section, we present a method to study quantitatively movements in the Beveridge curve. We decompose unemployment fluctuations into three categories; movements along the Beveridge curve due to changes in labor demand, shifts in the Beveridge curve due to unemployment inflows, and structural shifts due to shocks to matching efficiency.

2.1 Steady-state unemployment

Denote u_t and e_t the number of unemployed and employed individuals as a share of the labor force at instant $t \in \mathbb{R}_+$. Assume that all unemployed workers find a job according to a Poisson process with arrival rate λ_t^{UE} and that all employed workers lose their job according to a Poisson process with arrival rate λ_t^{EU}. There are no movements in and out of the labor force. In this context, the unemployment rate satisfies

$$\dot{u}_t = \lambda_t^{UE} e_t - \lambda_t^{EU} u_t \tag{1}$$

As first argued by Shimer (2007), the magnitudes of the two hazard rates is such that the half-life of a deviation of unemployment from its steady state value is about a month. As a result, at a quarterly frequency, the unemployment rate is very well approximated by its steady-state value u_t^{ss} so that

$$u_t \simeq \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \lambda_t^{UE}} \equiv u_t^{ss} \tag{2}$$

2.2 Modeling λ^{UE} with a matching function

The job finding rate is defined as the ratio of new hires to the stock of unemployed, so that the job finding rate can be written as $\lambda_t^{UE} = \frac{m_t}{u_t}$ with m_t the number of new matches at instant t. By modeling m_t with a constant returns to scale Cobb-Douglas matching function, a specification widely used in the search and matching literature (see e.g. Pissarides, 2001), we can express m_t as

$$m_t = m_0 u_t^{\sigma} v_t^{1-\sigma}$$

with m_0 a positive constant, v_t the number of job openings and u_t the number of unemployed.

In this context, we can model the job finding rate λ_t^{UE} as

$$\ln \lambda_t^{UE} = (1-\sigma) \ln \frac{v_t}{u_t} + m_0 + \nu_t. \tag{3}$$

2.3 Decomposing movements in the Beveridge curve

Writing the steady-state approximation for unemployment (2) and modeling the job finding rate with a matching function, we can write

$$u_t^{ss} \equiv \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \lambda_t^{UE}} \simeq \frac{\lambda_t^{EU}}{\lambda_t^{EU} + m_0 \left(\frac{v_t}{u_t^{ss}}\right)^{1-\sigma}} \tag{4}$$

Expression (4) is the theoretical underpinning of the Beveridge curve, the downward sloping relation between unemployment and vacancy posting. Steady-state unemployment moves along the Beveridge curve as firms adjust vacancies. In contrast, the Beveridge curve shifts when the unemployment inflow rate λ_t^{EU} moves.

However, while the matching function (3) is remarkably successful at modeling the job finding rate, the relation is not exact, and the labor market may temporarily deviate from its average matching efficiency. To separate movements along the Beveridge curve from shocks to the matching function, we define $u_t^{ss,bc}$, the steady-state unemployment rate implied by a stable Beveridge curve, i.e. by a stable matching function. Formally, $u_t^{ss,bc}$ is defined by

$$u_t^{ss,bc} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + m_0 \left(\frac{v_t}{u_t^{ss,BC}}\right)^{1-\sigma}}. \tag{5}$$

Denoting $\hat{\lambda}_t^{UE} = m0 \left(\frac{v_t}{u_t^{ss,bc}}\right)^{1-\sigma}$ the job finding rate predicted by a stable matching function, we can rewrite (2) as

$$u_t^{ss} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \hat{\lambda}_t^{UE} e^{\varepsilon_t}} \tag{6}$$

where $\varepsilon_t = \ln \lambda_t^{UE} - \ln \hat{\lambda}_t^{UE}$ captures deviations of the job finding rate from the value implied by a stable Beveridge curve, i.e. a stable relationship between unemployment and vacancies.

Log-linearizing (6) around the mean of λ_t^{EU}, $\hat{\lambda}_t^{UE}$ and ε_t, we get

$$\begin{aligned} d\ln u_t^{ss} &= (1-u^{ss})\left[d\ln\lambda_t^{EU} - d\ln\hat{\lambda}_t^{UE} - d\varepsilon_t\right] + \eta_t \\ &= d\ln u_t^{bc} + d\ln u_t^{shifts} + d\ln u_t^{eff} + \eta_t \end{aligned} \tag{7}$$

where $d\ln u_t^{bc} \equiv -(1-u^{ss})d\ln\hat{\lambda}_t^{UE}$ represents movements along the Beveridge curve, $d\ln u_t^{shifts} \equiv (1-u^{ss})d\ln\lambda_t^{EU}$ represents shifts in the Beveridge curve due to changes in unemployment inflows, and $d\ln u_t^{eff} \equiv (1-u^{ss})d\varepsilon_t$ captures the shifts in the Beveridge curve caused by changes in matching efficiency. The residual term η_t corresponds to the first-order approximation error.

We can then assess the separate contributions of the different movements of the Beveridge curve by noting as Fujita and Ramey (2009) that

$$Var\left(d\ln u_t^{ss}\right) = Cov(d\ln u_t^{ss}, d\ln u_t^{cyc}) + Cov(d\ln u_t^{ss}, d\ln u_t^{bc}) + Cov(d\ln u_t^{ss}, d\ln u_t^{eff}) + Cov(d\ln u_t^{ss}, \eta_t). \tag{8}$$

so that, for example, $\frac{Cov(d\ln u_t^{bc}, d\ln u_t^{ss})}{var(d\ln u_t^{ss})}$ measures the fraction of unemployment's variance due to movements along the Beveridge curve.

While a first-order approximation is very good on average, η_t becomes non-negligible with the high level of unemployment in the early 80s and in the 2008-2009 recession. Moreover, it will be interesting to decompose unemployment fluctuations relative to an arbitrary base year for which the first-order approximation can be more problematic. Instead, we will use a second-order approximation of steady-state unemployment. Fortunately, the expression remains simple because in practice all cross-order terms are negligible compared to $d^2\ln\lambda_t^{EU}$ and

$d^2 \ln \lambda_t^{UE}$. As a result, an excellent working approximation is given by the simple expression

$$\begin{aligned} d \ln u_t^{ss} &= (1-u^{ss}) d \ln \lambda_t^{EU} - \frac{1}{2}(1-u^{ss2}) d^2 \ln \lambda_t^{EU} \\ &\quad -(1-u^{ss}) d \ln \hat{\lambda}_t^{UE} + \frac{1}{2}(1-u^{ss})^2 d^2 \ln \hat{\lambda}_t^{UE} \\ &\quad -(1-u^{ss}) d\varepsilon_t + \frac{1}{2}\frac{\lambda^{EU}\lambda^{UE}}{\left(\lambda^{EU}+\lambda^{UE}\right)^2} d\varepsilon_t^2 + \tilde{\eta}_t \\ &= d \ln u_t^{bc} + d \ln u_t^{shift} + d \ln u_t^{eff} + \tilde{\eta}_t. \end{aligned} \tag{9}$$

An important advantage of being able to log-linearize around the mean or around an arbitrary date is that we do not need to detrend the data. That way, we will be able to study the high-frequency as well as the low-frequency movements in unemployment.

3 Some first results

3.1 Measuring individuals' transition rates

To identify the individuals' transition rates, we consider a general method valid for any number of labor market states belonging to the set S. A worker can be in different states, for example employed and unemployed. To identify the transition rates, we use CPS gross flows measuring the number of workers moving from state $A \in S$ to state $B \in S$ each month. To account for time aggregation bias, we consider a continuous environment in which data are available at discrete dates t and proceed as in Shimer (2007). Denote $N_t^{AB}(\tau)$ the number of workers who were in state A at $t \in \mathbb{N}$ and are in state B at $t+\tau$ with $\tau \in [0,1]$ and define $n_t^{AB}(\tau) = \frac{N_t^{AB}(\tau)}{\sum_{X \in S} N_t^{AX}(\tau)}$ the share of workers who were in state A at t.

Assuming that λ_t^{AB}, the hazard rate that moves a worker from state A at t to state B at $t+1$, is constant from t to $t+1$, $n_t^{AB}(\tau)$ satisfies the differential equation

$$\dot{n}_t^{AB}(\tau) = \sum_{C \neq B} n_t^{AC}(\tau)\lambda_t^{CB} - n_t^{AB}(\tau)\sum_{C \neq B} \lambda_t^{BC}, \qquad \forall\ A \neq B. \tag{10}$$

We then solve this system of differential equations numerically to obtain the transition rates. In the simpler case of only two labor force states E and U, the system of six equations simplifies to a system of two equations in $\dot{n}_t^{UE}$ and $\dot{n}_t^{EU}$ that we solve for λ_t^{EU} and λ_t^{UE}. We use data from the CPS covering 1967M6–2009m12 and calculate the quarterly series for the transition rates over 1967Q2-2009Q4 by averaging the monthly series.[1]

3.2 Estimating a matching function

We estimate a matching function over 1951-2009 by regressing

$$\ln \lambda_t^{UE} = (1-\sigma) \ln \frac{v_t}{u_t} + c + \nu_t \tag{11}$$

using our measure of the job finding rate λ^{UE} as the dependent variable.

We estimate (11) with monthly data using the composite help-wanted index presented in Barnichon (2010) as a measure of vacancy posting. We use non-detrended data over 1967:Q1-2009:Q4 and allow for first-order serial correlation in the residual. To take into account movements in the size of the labor force, we rescale the composite help-wanted index by the size of the labor force. Table 1 presents the result. First, we disregard the behavior of the labor market in the current recession and use data from 1967 until 2006 only. The elasticity σ is precisely estimated at 0.64, a value inside the plausible range $\sigma \in [0.5, 0.7]$ identified by Petrongolo and Pissarides (2001). A legitimate concern with this regression is that equation (3) may be subject to an endogeneity bias. We then estimate (3) using lagged values of v_t and u_t as instruments. As column (2) shows, the endogeneity bias appears to be small as the elasticity is little changed at 0.62.

We then turn to the behavior of the labor market in the 2008-2009 recession. In column (3), we use the whole sample 1967-2009. While the OLS point estimate declines only slightly at 0.62, the matching function cannot explain the magnitude of the drop in the job finding

[1]Before 1976, the microdata are not publicly available so we use the transition rates calculated by Shimer(2007) using Joe Ritter's tabulation of the gross flows from June 1967 to December 1975. The data are available at http://sites.google.com/site/robertshimer/research/flows.

rate in 2008 and 2009. Figure 1 plots the residual of equation (3) estimated over 1967-2009. While the matching function appears relatively stable over time, a testimony of the success of the matching function, the residual turns negative in 2008 and remains below zero until the end of the period. In the third quarter of 2009, the residual reached an all time low of three standard-deviations. While the matching function previously reached large negative values in 1979 or in the mid-80s, the residual averaged two standard-deviation below zero throughout 2008-2009. In column (4), we estimate a matching function over 2003-2009 only and find that the elasticity with respect to unemployment is significantly lower at 0.49.

These results point towards a change in matching efficiency, and in the rest of this section, we will explore the quantitative implications of this change for equilibrium unemployment.

3.3 Decomposing movements in the Beveridge curve

In this section, we decompose unemployment fluctuations in the Beveridge curve space. Using the Taylor expansion (9), we decompose unemployment fluctuations into: (i) movements along the Beveridge curve, (ii) shifts in the Beveridge curve, and (iii) shocks to the matching function. Importantly, in all exercises, none of the data are detrended.

To better visualize the contribution of each category in history, we log-linearize unemployment around the base year 1969. That base year is attractive because it corresponds to the highest reading for vacancy posting per capita as well as the lowest value for $\ln u_t^{shift}$.[2] Figure 2 plots (log) unemployment and its components relative to their 1969 values.

We first consider the impact of matching function shocks on the Beveridge curve. The shocks generally have a small impact on the equilibrium unemployment rate, a corollary of the success of the matching function in modeling the job finding rate. However, Figure 2 shows some marked decrease in matching efficiencies in the aftermath of the 74 and 82 peaks in unemployment. Without any loss in matching efficiency, the unemployment would have

[2] Thus, 1969 corresponds to the year with the most leftward Beveridge curve. 1969 also corresponds to a point where the matching function shock is very close to zero. In all, the base year 1969 is attractive because it can be used as a benchmark from which we can quickly visualize the rise and fall in trend unemployment as well as the cyclical fluctuations over the last 40 years.

been more than 50 basis points lower over 1984-1988 and 25 basis points lower over 1976-1980. The 2008-2009 recession is unique in the contribution of shocks to the matching function. The large decrease in matching efficiency previously documented is responsible for about 25 percent of the increase in unemployment since 2006Q4. This is more than twice as much as what happened during the early to mid 80s episode of double-digit unemployment. Had the matching function remained stable, the unemployment rate would have been 150 basis points lower in 2009, the largest shock to matching efficiency since 1967.

Comparing movements along the Beveridge curve and shifts in the Beveridge curve, Figure 2 suggests that both contribute roughly equally to unemployment's fluctuations. A variance decomposition exercise following (8) confirms this result. As shown in Table 2, movements along the Beveridge curve and shifts in the Beveridge curve account for respectively 48 and 42 percent of unemployment's variance. However, this result lumps together cyclical and secular movements. Figure 2 suggests that shifts in the Beveridge curve play a more important role at low frequencies. To separate trend and cyclical unemployment, we further decompose changes in unemployment into a trend component (from an HP-filter, $\lambda = 10^5$) and a cyclical component. Table 2 presents a variance decomposition exercise for each component. Shifts in the Beveridge curve account for more than 60 percent of unemployment's secular trend, but the situation is reversed at business cycle frequencies.

4 Controlling for individuals characteristics

The previous section suggests that at least 50 percent of cyclical unemployment fluctuations are due to movements along the Beveridge curve, i.e. to changes in labor demand. However, our framework is silent about the sources of Beveridge curve shifts, which play a non-trivial role at business cycle frequencies. In particular, some of the Beveridge curve shifts are caused by changes in labor demand as firms can shed workers during recessions, while others are caused by changes in quits, i.e. movements in labor supply.

Moreover, our framework is silent about the sources of changes in matching efficiency. For example, changes in the composition of the pool of unemployed could be responsible for some of the movements in matching efficiency. If a given category of the population with a lower than average job finding rate becomes overrepresented in the unemployment pool, the *average* job finding rate will decline because of a composition effect. Thus, it is important to control for worker heterogeneity when estimating a matching function.

To address these issues, this section extends our analysis by controlling for workers' heterogeneity in two ways. First, we proceed as in Section 3 but disaggregate the labor market flows by demographic groups and reason for unemployment (layoff or quit). Second, we use micro data on transitions across labor force states to estimate the probability of exiting or entering unemployment. This second approach allows us to control for a larger range of individuals' characteristics than is possible with macro data.

4.1 Disaggregating worker flows

In this section, we generalize our approach from Section 3 to different categories of workers ordered by sex, age and reason for unemployment.

4.1.1 Demographics

To allow for changes in the demographic composition of the labor force, we use CPS data to split workers into $N = 8$ categories; male vs. female in the three age categories 25-35, 35-45, 45-55, and male and female together for ages 16-25 and over 55. Since the differential equations (10) governing labor market flows hold independently for each age-sex category $i \in [1, N]$, we can estimate the hazard rates $\left\{\lambda_{t,i}^{AB}\right\}$ using the method described in Section 3. The aggregate hazard rates used in Section 3 can then be decomposed as

$$\begin{cases} \lambda_t^{UE} = \sum_{i=1}^{N} \frac{U_{it}}{U_t} \lambda_{it}^{UE} \simeq \sum_{i=1}^{N} \omega_{it} \frac{u_{it}^{ss}}{u_t^{ss}} \lambda_{it}^{UE} \\ \lambda_t^{EU} = \sum_{i=1}^{N} \frac{E_{it}}{E_t} \lambda_{it}^{EU} \simeq \sum_{i=1}^{N} \omega_{it} \frac{1-u_{it}^{ss}}{1-u_t^{ss}} \lambda_{it}^{EU} \end{cases} \tag{12}$$

where $\omega_{it} = \frac{LF_{it}}{LF_t}$ is the share of group i in the labor force and u_{it} the unemployment rate of group i. The steady-state unemployment rate for category i satisfies $u_{it}^{ss} = \frac{\lambda_{it}^{EU}}{\lambda_{it}^{EU}+\lambda_{it}^{UE}}$ since the differential equation (1) holds independently for each demographic group.

Log-linearizing (12), we get

$$\begin{cases} d\ln\lambda_t^{UE} = \sum_{i=1}^{N} \omega_i \frac{u_i^{ss}}{u^{ss}} \frac{\lambda_i^{UE}}{\lambda^{UE}} \left(d\ln\lambda_{it}^{UE} + d\ln\omega_{it}\frac{u_{it}^{ss}}{u_t^{ss}} \right) = d\ln\tilde{\lambda}_{it}^{UE} + d\ln\lambda_t^{UE,demog} \\ d\ln\lambda_t^{EU} = \sum_{i=1}^{N} \omega_i \frac{1-u_i^{ss}}{1-u^{ss}} \frac{\lambda_i^{EU}}{\lambda^{EU}} \left(d\ln\lambda_{it}^{EU} + d\ln\omega_{it}\frac{1-u_{it}^{ss}}{1-u_t^{ss}} \right) = d\ln\tilde{\lambda}_{it}^{EU} + d\ln\lambda_t^{EU,demog} \end{cases} \tag{13}$$

The first term in both equations corresponds to movements in $\tilde{\lambda}_t^{UE} = \sum_{i=1}^{N} \omega_i \frac{u_i^{ss}}{u^{ss}} \lambda_{it}^{UE}$ or $\tilde{\lambda}_t^{EU} = \sum_{i=1}^{N} \omega_i \frac{1-u_i^{ss}}{1-u^{ss}} \lambda_{it}^{EU}$, the hazard rate that holds the share of each demographic group constant. The second term, $d\ln\lambda_t^{UE,demog} \equiv \sum_{i=1}^{N} \omega_i \frac{u_i^{ss}}{u^{ss}} \frac{\lambda_i^{UE}}{\lambda^{UE}} d\ln\omega_{it}\frac{u_{it}^{ss}}{u_t^{ss}}$ or $d\ln\lambda_t^{EU,demog} \equiv \sum_{i=1}^{N} \omega_i \frac{1-u_i^{ss}}{1-u^{ss}} \frac{\lambda_i^{EU}}{\lambda^{EU}} d\ln\omega_{it}\frac{1-u_{it}^{ss}}{1-u_t^{ss}}$, corresponds to the composition effect, due to movements in the relative size of the labor force in each group ω_{it}, as well as changes in the share of each group in the unemployment pool $(\frac{u_i^{ss}}{u^{ss}})$ or in the employment pool $(\frac{1-u_i^{ss}}{1-u^{ss}})$. To illustrate the importance of controlling for changes in demographics, Figure 3 compares λ_t^{EU} and $\tilde{\lambda}_t^{EU}$, and shows that a significant fraction of the trend in λ_t^{EU} can be accounted for by demographics. Since young individuals have a higher turnover rate than older workers, the aging of the baby boom generation (which led to a decline in the share of young individuals in the labor force) explains some of the secular decline in the job separation rate.

4.1.2 Separating quits, temporary layoffs and permanent layoffs

Layoffs and quits are different labor market events that lead to shifts in the Beveridge curve. To separate these two concepts, we use the CPS micro data and classify jobless workers according to the event that led to their unemployment status: a permanent layoff p, a temporary layoff t, or a quit q.

There are three unemployment rates by reason: u^p, u^t and u^q and three sets of hazard rates $\{\lambda^{pE}, \lambda^{Ep}, \lambda^{qE}, \lambda^{Et}, \lambda^{tE}, \lambda^{Eq}\}$ as a job leaver may not have the same unemployment exit rate as a job loser. After obtaining the matched gross flows $\{N^{pE}, N^{Ep}, N^{qE}, N^{Et}, N^{tE}, N^{Eq}\}$ from CPS data, we correct for time aggregation bias using a version of (3) as in Section 3 to obtain the six transition rates. Figure 4 plots the result and shows that the hazard rates by reason for unemployment display a lot of heterogeneity. Job separation due to permanent or transitory layoffs do not display any evidence of a trend while job separation due to quits appear to follow a downward trend since the early 90s. Transitory layoffs seem to play a diminishing role in total separation and the 2008-2009 recession is striking in this respect. While λ_t^{Ep} increased rapidly to a record level, λ_t^{Et} remained 20 percent below its early 80s level. Not surprisingly, quits and especially temporary layoffs have a higher unemployment exit rate than permanent layoffs.

As in Section 3, in steady-state, the aggregate unemployment $u_t = \sum_{j\in\{p,t,q\}} u_t^j$ rate satisfies (2) with the average transition rates given by

$$\lambda_t^{UE} = \sum_{j\in\{p,t,q\}} \frac{u_t^{ss,j}}{u_t^{ss}} \lambda_t^{jE} \tag{14}$$

and

$$\lambda_t^{EU} = \sum_{j\in\{p,t,q\}} \lambda_t^{Ej}.$$

where $\left\{u_t^{ss,j}\right\}_{j\in\{p,t,q\}}$ is the steady-state unemployment rate for reason j. To solve for u_t^{ss} and $u_t^{ss,j}$, note that u_t^j satisfies $\dot{u}_t^j = \lambda_t^{UE}(1 - \sum_{j\in\{p,t,q\}} u_t^j) - \lambda_t^{Ej} u_t^j$, $\forall\ j \in \{p,t,q\}$ so that in steady-state, $\left\{u_t^{ss,j}\right\}_{j\in\{p,t,q\}}$ is the solution of the system given by $\left\{\dot{u}_t^j = 0\right\}_{j\in\{p,t,q\}}$.[3]

Expression (14) highlights the importance of the composition effect on movements in the average job finding rate. The average job finding rate depends on each group's job finding rate

[3] Formally, a little bit of algebra gives us $u_t^{ss} = \frac{\sum_{j\in\{p,t,q\}} \lambda_t^{Ej} \prod_{j\neq i} \lambda_t^{jE}}{\sum_{j\in\{p,t,q\}} \lambda_t^{Ej} \prod_{j\neq i} \lambda_t^{jE} + \prod_{j\in\{p,t,q\}} \lambda_t^{jE}}$ and $u_t^{ss,j} =$

but also on the composition of the unemployment pool. If the share of permanent job losers (the ones with the lowest unemployment exit rate) increases more than usual in a recession (as it appears to be the case in the current recession), the average job finding rate will decline more than usual, and an approach that does not control for composition will interpret this result as lower matching efficiency.

Log-linearizing (14), we get

$$d\ln \sum_{j\in\{p,t,q\}} \frac{u_t^{j,ss}}{u_t^{ss}}\lambda_t^{jE} = \sum_{j\in\{p,t,q\}} \frac{u^{j,ss}}{u^{ss}}\frac{\lambda^{jE}}{\lambda^{UE}} d\ln \lambda_t^{jE} + \sum_{j\in\{p,t,q\}} \frac{u^{j,ss}}{u^{ss}}\frac{\lambda^{jE}}{\lambda^{UE}} d\ln \frac{u_t^{j,ss}}{u_t^{ss}} \tag{15}$$

The first term is the job finding rate holding the share of each unemployment rate constant, and the second term is the composition effect. After a bit of algebra, we can rewrite the composition effect as

$$d\ln \lambda_t^{UE,reason} = \sum_{j\in\{p,t,q\}} \frac{u^{j,ss}}{u^{ss}}\left(\frac{\lambda^{jE}}{\lambda^{UE}}-1\right) d\ln \lambda_t^{Ej} + \sum_{j\in\{p,t,q\}}\sum_{i\neq j} \frac{u^{j,ss}}{u^{ss}}\left(\frac{\lambda^{iE}}{\lambda^{UE}}-1\right) d\ln \lambda_t^{jE} \tag{16}$$

The first term of (16) captures the effect of movements in the job separation rate of a subgroup that differs from the average job finding rate by $\frac{\lambda^{jE}-\lambda^{UE}}{\lambda^{UE}}$. An increase in the job separation rate of permanent job losers lowers the average job finding rate because this category of unemployed has a lower than average job finding rate $\lambda^{jE}-\lambda^{UE}<0$. The second term captures the impact of a change in the job finding rate. If the job finding rate of a job leavers increases, this will lower the fraction of unemployment due to quits and may lower the job finding rate as the share of other categories (with a lower than average job finding rate) increases.

To illustrate the importance of controlling for composition changes, Figure 5 compares λ_t^{UE} and $\tilde{\lambda}_t^{UE}$, the job finding rate holding the share of each unemployment rate (by reason)

$u_t^{ss}\dfrac{\lambda_t^{Ej}\prod_{j\neq i}\lambda_t^{jE}}{\sum_{j\in\{p,t,q\}}\lambda_t^{Ej}\prod_{j\neq i}\lambda_t^{jE}}.$

constant. We can see that a sizeable fraction of the dramatic decline in λ_t^{UE} in the 2008-2009 recession is due to the composition effect. Unlike in the early-80s recession, the contribution of temporary layoffs to total job separation in 2008-2009 is a lot smaller. In contrast, the fraction of permanent layoffs is at its highest level since 1976. Since workers from the latter group have a much lower job finding rate, their "overrepresentation" in the unemployment pool is partly responsible for the lower than usual average job finding rate. The 2001 recession also saw a relatively high contribution of permanent layoffs so that a sizeable fraction of the decline the average job finding rate is due to a composition effect.

Since composition accounts for a non-trivial fraction of movements in the job finding rate and can exaggerate the effect of movements in labor market tightness on λ^{UE}, we reestimate a matching function on $\tilde{\lambda}_t^{UE}$. Table 1 shows the results of the regression $d\ln\tilde{\lambda}_t^{UE} = (1-\sigma)d\ln\frac{v_t}{u_t} + \varepsilon_t$. We can see that the estimated elasticity is higher, indicating that the characteristics of the unemployed worsen during recessions. Moreover, the composition effect appears to explain a sizeable fraction of the decrease in matching efficiency since 2002. Figure 5 plots the fitted value $m_0\left(\frac{v_t}{u_t}\right)^{1-\sigma}$ alongside $\tilde{\lambda}_t^{UE}$ and λ_t^{UE}. This time the matching function is broadly consistent with the behavior of $\tilde{\lambda}_t^{UE}$ in the 2008-2009 recession and explains a larger fraction of the decline in the job finding rate since 2002.

4.1.3 Combining demographics and reason for unemployment

Since each demographic group evolves independently of the other, it is relatively straightforward to simultaneously disaggregate by demographics and reason for unemployment. The disaggregation by reason presented above is valid for each group i, so we can write

$$\begin{cases} d\ln\lambda_{it}^{UE} = d\ln\sum_{j\in\{p,t,q\}}\frac{u_i^{j,ss}}{u_i^{ss}}\lambda_{it}^{jE} \\ d\ln\lambda_{it}^{EU} = d\ln\sum_{j\in\{p,t,q\}}\lambda_{it}^{Ej} \end{cases} \qquad \forall \;\; i\in[1,N]$$

Summing across demographic groups and combining (13) with (15), we get

$$\begin{cases} d\ln\lambda_t^{UE} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{u_i^{j,ss}}{u}\frac{\lambda_i^{jE}}{\lambda^{UE}} d\ln\lambda_{it}^{jE} + \sum_{i=1}^{N} d\ln\lambda_{it}^{UE,reason} + d\ln\lambda_t^{UE,demog} \\ \qquad = d\ln\tilde{\lambda}_t^{UE} + d\ln\lambda_t^{UE,reason} + d\ln\lambda_t^{UE,demog} \end{cases} \tag{17}$$

and

$$\begin{cases} d\ln\lambda_t^{EU} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{1-u_i^{ss}}{1-u^{ss}}\frac{\lambda_i^{Ej}}{\lambda^{EU}} d\ln\lambda_{it}^{Ej} + d\ln\lambda_t^{EU,demog} \\ \qquad = d\ln\tilde{\lambda}_t^{EU} + d\ln\lambda_t^{UE,demog} \end{cases}$$

The first term in (17) corresponds to movements in $\tilde{\lambda}_t^{UE} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{u_i^{j,ss}}{u^{ss}}\lambda_{it}^{jE}$ the job finding rate that holds the unemployment share of each demographic group constant as well as the share of each unemployment rate (by reason) constant. Similarly, $\tilde{\lambda}_t^{EU} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{1-u_i^{ss}}{1-u^{ss}}\lambda_{it}^{Ej}$ is the job separation rate that holds the share of each demographic group constant.

4.2 Using micro data to estimate labor force transitions

The preceding section highlighted the importance of accounting for individual characteristics in order to better understand changes in matching efficiency and shifts in the Beveridge curve. While controlling for demographics and reason for unemployment helped to explain some of the apparent decline in matching efficiency in the 2008-2009 recession, Figure 5 shows that the matching function still overpredicts the job finding rate since 2001.

To control for a larger range of individuals' characteristics, we turn to micro data and explore whether individuals heterogeneity can account for some of the shifts in the matching function as well as some of the movements along the Beveridge curve. We use micro data on transitions across labor force states from the CPS to estimate which characteristics make exit from unemployment less likely, and which characteristics make employment separation (layoff or quit) more likely. Then we estimate whether the observable characteristics of the unemployed have changed in a way that could explain the decline in matching efficiency since

2001.

4.2.1 UE Transition rates

We use matched CPS data to estimate individual's i transition probability from unemployment to employment λ_i^{UE}.

The following explanatory variables appear to be robustly associated with an individual's probability of escaping unemployment: *reason for becoming unemployed, unemployment in the individual's state of residence, job openings in the industry in which the individual was previously employed, age, sex,* and *the current duration of unemployment.*

The duration of unemployment could represent true duration dependence due, perhaps, to scarring effects; more likely, it represents unobserved heterogeneity in hazard rates, as individuals with low unobserved hazard rates become over time disproportionately represented in the group of unemployed workers with relatively long durations. When estimating the effect of duration on UE transition rates, it is important to control for aggregate labor market conditions. The ability of duration to proxy for scarring or worker heterogeneity may be weaker in recessions, when durations for all workers tends to increase, than in expansions. Thus, in our specification we interact the duration of unemployment with average duration.

We also include a set of monthly dummies to control for seasonality in exit hazards and a measure of labor market tightness. We choose the parameterization of the latter variable and the functional form of the estimating equation so that estimates are comparable with the estimates of aggregate matching function parameters from previous sections. Specifically, we use a logit specification. The logit function has the property that the effect of an explanatory variable on the odds ratio is constant and equal to the exponentiated estimated parameter of that variable. Specifically,

$$O_{it}(X_t) = \frac{p}{1-p} = \frac{\frac{e^{X\beta}}{1+e^{X\beta}}}{1 - \frac{e^{X\beta}}{1+e^{X\beta}}} = e^{X\beta}$$

where $O_{it}(X_i, t)$ is the odds ratio for individual i at time t, and X_t denotes individual i's characteristics.

If we choose the measure of labor market tightness to be the log of the odds ratio for the aggregate matching function and constrain the logit parameter associated with it to equal 1, i.e.

$$X_{1,t} = \ln \frac{m_0 \left(\frac{v_t}{u_t}\right)^{1-\sigma}}{1 - m_0 \left(\frac{v_t}{u_t}\right)^{1-\sigma}} \text{ with } \beta_1 = 1 \tag{18}$$

we get that the change in the odds ratio for an individual with identical characteristics across different labor market states is equal to the change in the odds ratio as computed using the aggregate matching function.

$$\frac{O_t^i(X_i, t)}{O_{it-1}(X_i, t-1)} = \frac{\frac{m_0\left(\frac{v_t}{u_t}\right)^{1-\sigma}}{1-m_0\left(\frac{v_t}{u_t}\right)^{1-\sigma}}}{\frac{m_0\left(\frac{v_{t-1}}{u_{t-1}}\right)^{1-\sigma}}{1-m_0\left(\frac{v_{t-1}}{u_{t-1}}\right)^{1-\sigma}}}$$

In other words, with the logit specification and the variable reflecting labor market tightness equal to $X_{1,t}$ in (18), there is a congruence between the effect of labor market tightness on the probability of an individual exiting unemployment as estimated using aggregate data and the same estimate using individual-level data.

To illustrate this point, we aggregate the individual level unemployment exits in each month and estimate a matching function using aggregated data, weighting each monthly aggregated observation by the number of individual observations underlying it. Then we compare the estimated parameters from this aggregate regression to the same parameters estimated using maximum likelihood on the individual level data with the labor market tightness variable defined as X_1 and its coefficient constrained to equal 1. As shown in Table 3, the estimated matching function parameters are nearly identical.

The importance of controlling for individual-level characteristics We now estimate the aggregate matching function parameters using the individual data and controlling for the individual-level characteristics described above. We perform this estimation on three sets of data. The first data set uses JOLTS job openings to measure vacancies and, thus the time period is limited to 2001-2007. We exclude 2008 and 2009 to prevent the aggregate matching function parameters from being biased by the apparent outward shifts in the Beveridge curve over these years due to changes in the matching function that could be correlated with changes in aggregate labor market tightness. One advantage of the JOLTS data set is that it allows us to measure vacancies at the industry level and control for the effect of the concentration of unemployment in stagnant industries on aggregate matching efficiency. Our second data set extends back to 1994, when a redesign of the CPS improved the quality of labor force transitions. In this data set, we use the composite HWI to measure vacancies. Our third data set extends back to 1976 and again uses the composite HWI to measure vacancies. Because of changes in the CPS data due to the 1994 redesign, we estimate separate coefficients on individual characteristics for observations before and after 1994, but constrain the aggregate matching function parameters to be constant throughout the sample period.

Column 1 of Table 4 presents estimates from the first data set. First, note the change in the aggregate matching function parameters once we control for individual characteristics. The elasticity of the probability of exit with respect to the vacancy-unemployment ratio, $1-\sigma$, falls by about 1/3 relative to elasticities estimated using aggregate data or using individual data but not controlling for individual characteristics.

This result confirms and extends Section 4.1's finding that changes in the composition of unemployment pool can bias matching function estimates. Estimates of matching function parameters using aggregate data implicitly assume that average characteristics of the unemployed are not correlated with the vacancy-unemployment ratio. The effect of average individual characteristics on average exit probabilities are subsumed in the error term of the aggregate estimating equation. If these characteristics change over time and these changes are correlated with changes in the aggregate vacancy-unemployment ratio, then estimates of matching function parameters using aggregate data will be biased.

Controlling for a wide range of individuals characteristics lowers $1-\sigma$ significantly and indicates that estimates of matching function parameters using aggregate data are biased upward because characteristics of the unemployed worsen in recessions.

Columns 2 and 3 of Table 4 perform the same estimation with the second and third datasets discussed above, respectively. The results are qualitatively similar: the matching function elasticity is considerably reduced when estimation is performed with individual-level data because the effect of individual characteristics on exit hazards is procyclical.

Contributions of individual characteristics Next, we examine which characteristics of the unemployed are most responsible for causing composition effects to be procyclical. The predicted average exit rate $\hat{\lambda}_t^{UE}$ is

$$\hat{\lambda}_t^{UE} = \sum_i \varkappa_{it} \lambda^{UE}\left(X_{it}, \theta_t; \hat{\beta}\right) \tag{19}$$

with $\varkappa_{it}$ the share of unemployed with characteristics X_{it} and $\hat{\beta}$ the estimated parameters. Taking a first order approximation of (19), one can decompose E_t^p into components attributable to changes in each of the observable characteristics. For example, if X_{it} is a vector of J observable characteristics indexed by j, then the contribution of characteristic j is

$$\begin{aligned}
\hat{\lambda}_t^{UE} &\simeq \sum_i \omega_{it} \left[\sum_j \left. \frac{\partial \lambda^{UE}\left(X_{it}, \theta_t = \bar{\theta}; \hat{\beta}\right)}{\partial X_{it}^j} \right|_{X_{it}=\bar{X}} \left(X_{it}^j - \bar{X}_{it}^j\right) + \hat{\lambda}_{it}^{UE,\theta} \right] \\
&\simeq \sum_j \hat{\lambda}_t^{UE,j} + \hat{\lambda}_t^{UE,\theta}
\end{aligned} \tag{20}$$

with $\hat{\lambda}_t^{UE,j} = \sum_i \omega_{it} \left. \frac{\partial f\left(X_{it}, \theta_t = \bar{\theta}; \hat{\beta}\right)}{\partial X_{it}^j} \right|_{X_{it}=\bar{X}} \left(X_{it}^j - \bar{X}_{it}^j\right)$ and $\hat{\lambda}_t^{UE,\theta}$ is the contribution of the aggregate labor market tightness. The first order approximation does a good job tracking the change in the hazard due to unemployment composition, suggesting that the decomposition

(20) will be informative.

We use the JOLTS measure of vacancies and decompose the composition effect into five components: reason for unemployment (which captures the increasing share of permanent job losers), demographic effects (age and sex), unemployment duration, unemployment in the individual's state of residence, and concentration of unemployment in stagnant industries (those with low rates of job openings). Since the contribution of demographics is very small, Figure 6 plots the contribution of the four other characteristics along with the total composition effect. The unemployment rate in the state of residence is the most important factor, accounting for more than 50 percent of the total composition effect. This is particularly true in the 2008-2009 recession. Unemployed workers are concentrated in states with higher than average unemployment rate, i.e. in states with lower than average job finding probabilities. These pockets of very high unemployment rate drive down the average job finding rate. Reason for unemployment contributes to about 25 percent of the total composition effect. As we saw in Section 4.1, the fact that permanent job losers have become a larger fraction of the unemployed has also lowered the average job finding rate. The higher share of long-term unemployed also explain some of the composition effect. Finally, the increasing concentration of the unemployed in stagnant industries can also play a role, accounting for about 10 percent of the total composition effect in the 2008-2009 recession.

Can individual characteristics explain the shifts in the matching function? Next, we ask whether accounting for the characteristics of the unemployed can explain the shifts in the aggregate matching function estimated in Section 3.[4]

Combining (7) with (20), we can write an approximate decomposition of the shifts in the matching function into (1) a component due to changes in the composition of unemployment (2) shifts not accounted for by composition changes, and (3) an error term capturing the difference between adjusted flows data (which we use for this decomposition) and the unadjusted data,

[4]Since the estimation of matching shifts uses aggregated (unadjusted) micro data but some of the individual characteristic' measures are based on published (adjusted) BLS data, we verified that parameter estimates were similar using the aggregated individual level data (unadjusted data) or the published data on labor force flows.

which we use to measure composition effects.

Figure 7 plots the decomposition using the HWI measure of vacancy and shows that until 2006, almost all of the cyclical shifts in the matching function are due to composition changes.[5] After 2006, composition explains about half of the total decline in matching efficiency.

4.2.2 EU Transition rates

Next, we turn to estimating transitions from employment to unemployment. Because transitions from employment to unemployment resulting from a quit and transitions resulting from a layoff are affected differently by characteristics of workers and by the state of the aggregate economy, we specify the transition as a multinomial logit with three outcome: no transition, transition to unemployment via layoff and transition to unemployment via quit. Age and sex likely influence these transition rates as does the level of aggregate labor demand, which we proxy for using the log of the aggregate vacancy rate. Davis, Faberman, and Haltiwanger (2006) described a non-linearity in firms' layoff functions. If firms have postive net employment growth, layoffs decrease slightly as net employment growth declines. If firms have negative net employment growth, layoffs increase strongly as net employment growth declines. To allow for a non-linearity in layoff behavior as a greater proportion of firms become net job destroyers, we also include a quadratic term for the log vacancy rate. The JOLTS data also enable us to include the deviation and squared deviation of the vacancy rate in the workers' industry from the aggregate vacancy rate. Finally, some industries have persistently higher turnover than others, leading to a persistently higher level of layoffs or quits. We use the average rate of job openings in an industry to proxy for average turnover.

Table 5 shows results from the estimation of the multinomial logit. With the exception of the average vacancy rate, all variables are significant at the 5 percent level in predicting a layoff transition. In contrast, only the age variables and the average vacancy rate variable are significant in predicting quits. The coefficient on the aggregate vacancy rates indicates that

[5] Results are very similar using JOLTS data.

layoffs are highly countercyclical; quits are mildly procyclical though the coefficient on the aggregate vacancy rate is not statistically significant.

Contributions of individual characteristics Next, using a similar first-order decomposition of (19), we decompose movements of EU transitions rates into contributions from age, sex, industry demand, and aggregate demand. Consistent with the findings from Section 4.1, the gradual aging of the labor force has pushed the separation rate lower of the the past 15 years. About 2/3 of the aging effect has occurred through reduced layoffs and about 1/3 through lower quits. Given that quits are about 1/5 of layoffs on average, this implies a larger effect of aging on quits than layoffs. Changes in gender composition have had very little effect on EU transitions. By far the largest contributor to changes in EU transitions is changes in labor demand, as proxied by changes in aggregate and industry vacancy rates. Results using JOLTS data show that most of the demand effect occurs through the aggregate vacancy rate. Although industry-level demand is important in predicting individual-level layoffs, it is not a significant contributor to cyclical increases in layoffs.

5 Allowing for entry and exit from the labor force

In order to interpret shifts in the Beveridge curve, it is important to include movements in and out of the labor force as those can be a non-negligible determinant of unemployment fluctuations, especially at low frequency (see e.g. Abraham and Shimer, 2001). In this section, we generalize our approach from Section 3 by allowing for movements in and out of the labor force. First, we present a simple decomposition using average hazard rates. Second, we control for worker heterogeneity (demographics and reason for unemployment) in a similar fashion to the two labor market states decomposition.

5.1 Using aggregate hazard rates

We first ignore worker heterogeneity and proceed as in Section 3. Denote U_t, E_t, and I_t the number of unemployed, employed and inactive individuals at instant $t \in \mathbb{R}_+$. Denoting λ_t^{AB} the hazard rate of transiting from state $A \in \{E, U, I\}$ to state $B \in \{E, U, I\}$, unemployment, employment and inactivity will satisfy the system of differential equations

$$\begin{cases} \dot{U}_t = \lambda_t^{EU} E_t + \lambda_t^{IU} I_t - (\lambda_t^{UE} + \lambda_t^{UI}) U_t \\ \dot{E}_t = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - (\lambda_t^{EU} + \lambda_t^{EI}) E_t \\ \dot{I}_t = \lambda_t^{EI} E_t + \lambda_t^{UI} U_t - (\lambda_t^{IE} + \lambda_t^{IU}) I_t \end{cases} \tag{21}$$

Again, Shimer (2007) showed that the unemployment rate $\frac{U_t}{LF_t}$ is very well approximated by its steady-state value ($\dot{U}_t = \dot{E}_t = \dot{I}_t = 0$) equal to

$$u_t^{ss} \equiv \frac{s_t}{s_t + f_t} \tag{22}$$

with s_t and f_t defined by

$$\begin{cases} s_t = \lambda_t^{EI} \lambda_t^{IU} + \lambda_t^{IE} \lambda_t^{EU} + \lambda_t^{IU} \lambda_t^{EU} \\ f_t = \lambda_t^{UI} \lambda_t^{IE} + \lambda_t^{IU} \lambda_t^{UE} + \lambda_t^{IE} \lambda_t^{UE} \end{cases}$$

Similarly to Section 3, log-linearizing (22) gives us[6]

$$\begin{aligned} d \ln u_t^{ss} &= \alpha^{EI} d \ln \lambda_t^{EI} + \alpha^{IU} d \ln \lambda_t^{IU} + \alpha^{EU} d \ln \lambda_t^{EU} \\ &\quad - \alpha^{IE} d \ln \lambda_t^{IE} - \alpha^{UI} d \ln \lambda_t^{UI} - \alpha^{UE} d \ln \lambda_t^{UE} + \eta_t \end{aligned} \tag{23}$$

[6] Contrary to the two labor market states, a first-order Taylor expansion already gives an excellent approximation of deviations of unemployment from its mean. This is due to the fact that compared to (7), (23) splits $d \ln u_t^{ss}$ into smaller pieces, which then deviate less from their mean.

with $\{\alpha^{AB}\}$ some positive constants depending on the mean of $\{\lambda_t^{AB}\}$.[7] In this context, shifts in the Beveridge curve are given by

$$d\ln u_t^{shift} = \alpha^{EU} d\ln\lambda_t^{EU} + \alpha^{EI} d\ln\lambda_t^{EI} + \alpha^{IU} d\ln\lambda_t^{IU} - \alpha^{IE} d\ln\lambda_t^{IE} - \alpha^{UI} d\ln\lambda_t^{UI} \qquad (24)$$

5.2 Allowing for worker heterogeneity

Using the same logic as in Section 4, we can refine (24) by disaggregating worker flows by reason for unemployment and demographics.

Each demographic group i verifies the system of differential equations (21) where the transition rates are given by $\{\lambda_{it}^{AB}\}$, and steady-state unemployment of group i is given by $u_{it}^{ss} \equiv \frac{s_{it}}{s_{it}+f_{it}}$ with s_{it} and f_{it} defined as in (22).

To disaggregate by reason for unemployment, we classify jobless workers according to the event that led to their unemployment status: a permanent layoff p, a temporary layoff t, a quit q and a labor force entrance o. Formally, for each demographic group i, there are four unemployment rates by reason: u_i^p, u_i^t, u_i^q and u_i^o and the associated hazard rates due to employment separation $\{\lambda_i^{jE}, \lambda_i^{Ej}, \lambda_i^{jI}\}$, $j \in \{p,t,q\}$ or labor force entrance $\{\lambda_i^{oE}, \lambda_i^{Io}, \lambda_i^{oI}\}$.

The aggregate unemployment rate u_t^{ss} satisfies (22) and, similarly to the two labor market states case, the average transition rates can be decomposed as

$$\begin{cases} \lambda_t^{UB} = \sum_{i=1}^{N} \sum_{j\in\{p,t,q\}} \omega_{it} \frac{u_{it}^{j,ss}}{u_t^{ss}} \lambda_{it}^{jB}, \quad B \in \{E, I\} \\ \lambda_t^{EU} = \sum_{i=1}^{N} \sum_{j\in\{p,t,q\}} \omega_{it} \frac{e_{it}^{ss}}{e_t^{ss}} \lambda_{it}^{Ej} \text{ and } \lambda_t^{EI} = \sum_{i=1}^{N} \omega_{it} \frac{e_{it}^{ss}}{e_t^{ss}} \lambda_{it}^{EI} \\ \lambda_t^{IU} = \sum_{i=1}^{N} \omega_{it} \frac{i_{it}^{ss}}{i_t^{ss}} \lambda_{it}^{Io} \text{ and } \lambda_t^{IU} = \sum_{i=1}^{N} \omega_{it} \frac{i_{it}^{ss}}{i_t^{ss}} \lambda_{it}^{EI} \end{cases} \qquad (25)$$

Because Beveridge curve shifts due to job separation can be caused by labor demand

[7]Formally, $\alpha^{EI} = (1-\bar{u}^{ss})\frac{\lambda^{EI}\lambda^{IU}}{s}$, $\alpha^{UE} = \frac{\lambda^{IU}\lambda^{UE}+\lambda^{IE}\lambda^{UE}}{s+f}$, $\alpha^{IE} = \frac{\lambda^{IE}\lambda^{EU}}{s}(1-\bar{u}^{ss}) - \frac{\lambda^{UI}\lambda^{IE}+\lambda^{IE}\lambda^{UE}}{s+f}$, $\alpha^{UI} = \frac{\lambda^{UI}\lambda^{IE}}{s+f}$, $\alpha^{EU} = (1-\bar{u}^{ss})\frac{\lambda^{IE}\lambda^{EU}+\lambda^{IU}\lambda^{EU}}{s}$, $\alpha^{IU} = (1-\bar{u}^{ss})\frac{\lambda^{EI}\lambda^{IU}+\lambda^{IU}\lambda^{EU}}{s} - \frac{\lambda^{IU}\lambda^{UE}}{s+f}$.

movements (layoffs) or labor supply movements (quits), it is useful to treat these two events separately. We further decompose λ_t^{EU} into $\lambda_t^{EU} = \lambda_t^{Ept} + \lambda_t^{Eq}$ with $\lambda_t^{Ept} = \sum_{i=1}^{N} \sum_{j \in \{p,t\}} \omega_i \frac{u_i^{j,ss}}{u^{ss}} \lambda_{it}^{jE}$ and $\lambda_t^{Eq} = \sum_{i=1}^{N} \omega_i \frac{u_i^{q,ss}}{u^{ss}} \lambda_{it}^{qE}$.

Proceeding as in Section 4, we can isolate the movements in the average hazard rates $\{d \ln \lambda_t^{AB}\}$ due to the composition effect. Log-linearizing the average hazard rates, we can write

$$\begin{cases} d \ln \lambda_t^{UB} = d \ln \tilde{\lambda}_t^{UB} + d \ln \lambda_t^{UB,reason} + d \ln \lambda_t^{UB,demog}, & B \in \{E, I\} \\ d \ln \lambda_t^{EB} = d \ln \tilde{\lambda}_t^{EB} + d \ln \lambda_t^{EB,demog}, & B \in \{pt, q, I\} \\ d \ln \lambda_t^{IB} = d \ln \tilde{\lambda}_t^{IB} + d \ln \lambda_t^{IB,demog}, & B \in \{U, E\} \end{cases} \tag{26}$$

where $\left\{\tilde{\lambda}_t^{AB}\right\}$ are defined as in Section 4 and denote the transition rates that hold the composition (demographics and reason for unemployment) of the unemployment pool, employment pool and inactivity pool constant. Similarly, $d \ln \lambda_{it}^{AB,demog}$ and $d \ln \lambda_{it}^{UA,reason}$ are defined as in Section 4.[8]

5.3 Interpreting shifts in the Beveridge curve

We now combine sections 5.1 and 5.2 to interpret the movements in the Beveridge curve since 1976. Combining (24) and (26), we can decompose shifts in the Beveridge curve into four components: (i) changes in labor demand (permanent and temporary layoffs), (ii) the effect of demographics on layoffs, (iii) changes in labor supply (due to quits and movements in and out of the labor force), and (iv) the composition effect of movements in demographics and reason for unemployment on labor supply. Formally:

$$d \ln u_t^{shifts} = d \ln u_t^{L^d shifts} + d \ln u_t^{L^d shifts,comp} + d \ln u_t^{L^s shifts} + d \ln u_t^{L^s shifts,comp} \tag{27}$$

[8] See the Appendix for the expressions for $\tilde{\lambda}_t^{AB}$, $d \ln \lambda_t^{AB,demog}$ or $d \ln \lambda_t^{UA,reason}$.

where

$$\begin{cases} d\ln u_t^{L^d shifts} = \alpha^{EU} d\ln \tilde{\lambda}_t^{Ept} \\ d\ln u_t^{L^d shifts,comp} = \alpha^{EU} d\ln \lambda_t^{Ept,demog} \\ d\ln u_t^{L^s shifts} = \alpha^{EI} d\ln \tilde{\lambda}_t^{EI} + \alpha^{IU} d\ln \tilde{\lambda}_t^{IU} + \alpha^{EU} d\ln \tilde{\lambda}_t^{Eq} - \alpha^{IE} d\ln \tilde{\lambda}_t^{IE} - \alpha^{UI} d\ln \tilde{\lambda}_t^{UI} \\ d\ln u_t^{L^s shifts,comp} = \alpha^{EI} d\ln \lambda_t^{EI,demog} + \alpha^{IU} d\ln \lambda_t^{IU,demog} + \alpha^{EU} d\ln \lambda_t^{Eq,demog} \\ \qquad -\alpha^{IE} d\ln \lambda_t^{IE,demog} - \alpha^{UI} \left(d\ln \lambda_t^{UI,reason} + d\ln \lambda_t^{UI,demog} \right) \end{cases}$$

Table 6 present the results of a variance decomposition exercise for $d\ln u_t^{shifts}$. Looking first at the raw data suggests that labor demand and labor supply are equally responsible for Beveridge curve shifts, accounting for one third of the variance each and composition effects accounting for the remaining third. However, this conclusion changes drastically when one considers high and low-frequency movements separately: labor supply is the prime driving force of secular shifts in the Beveridge curve but labor demand is the main driving force at business cycle frequencies. We now discuss each frequency range separately.

Low-frequency movements: Labor supply, including the composition effect due to demographics, accounts for almost 80 percent of the total variance in secular Beveridge curve shifts. This result is due to two factors: the aging of the baby boom and the increase in women's labor force participation rate.[9]

The right panel of Figure 8 plots the trends in $d\ln u_t^{L^s shifts,comp}$ for six demographic groups and shows that the decline in the share of young workers (male and female) contributed to the trend in unemployment. Indeed, younger workers have higher turnover and a higher unemployment rate than prime age or old workers and a decline in the youth share automatically reduces the aggregate unemployment rate. The other influential demographic change, this time with a negative effect on unemployment, was the large increase in prime age female's labor force participation rate until the mid-90s that dampened the baby boom's effect.

[9] The 18 percent contribution of $d\ln u_t^{L^d\ shifts,comp}$ is the result of the increasing use of permanent layoffs at the expense of temporary layoffs since early 2000.

The left panel of Figure 8 plots the trends in $d\ln u_t^{L^s shifts}$ for six demographic groups and highlights a downward trend in unemployment caused by a change in the behavior of women. To help understand this phenomenon, Figure 9 plots the behavior of prime age women's transition rates over 1976-2009. Two changes are apparent.[10] First, the secular increase in λ^{IU} until the mid-90s and the secular increase in λ^{IE} are due to more women joining the labor force, either by directly finding a job (as is increasingly the case) or by going first through the unemployment pool. Second, women display an increasing attachment to the labor force as λ^{UI} and λ^{EI} follow downward trends since 1976, meaning that women are increasingly likely to join or remain in the unemployment pool after an employment spell rather than drop out of the labor force. Finally, the downward trend in quits mentioned in Section 4 can be traced back to a secular decline in the quit rate of women, possibly due to their increased attachment to the labor force.[11]

Since trends are of consequence for the future locus of the Beveridge curve in the years to come, two more recent labor supply trends are worth mentioning. First, Figure 10 plots the transition rates for women aged over 55. A trend apparent since the late 90s is the increasing labor force participation of older women as both λ^{IU} and λ^{IE} are following upward trends. We can also notice an increase in labor force attachment as both λ^{UI} and λ^{EI} are following downward trends. The same result holds for men over 55. Second, Figure 12 shows that young workers are less likely to join the labor force ($\lambda^{IE}$and λ^{IU} are both on downward trends since the mid-90s). This could be related to the increase in the number of years of education as young workers stay longer in school before joining the labor force.

In contrast to labor supply, labor demand plays almost no role at low frequencies (a corrolary of the absence of any significant trend in the layoff rate). However, the aging of the baby boom generation caused the average layoff rate to decline (as younger workers have the highest turnover rates), and explains why $d\ln u_t^{L^d shifts,comp}$ accounts for 18 percent of the secular leftward shift in the Beveridge curve.

[10] Abraham and Shimer (2001) were the first to notice these two changes using annual transition probabilities.
[11] In contrast, men's quit rate displays little trend.

Business cycle fluctuations: Turning to cyclical frequencies, labor demand accounts for 65 percent of the variance in Beveridge curve shifts. Labor supply still accounts for 25 percent of total shifts as workers (in particular women) are more likely to join/stay in the labor force during recessions (Figure 10 and 12), contributing to increase the unemployment rate.

In the current recession, three labor supply changes are worth mentioning. First, prime age male display an exceptional attachment to the labor force with λ^{IU} and λ^{UI} showing record movements in Figure 11. This could be due to the Extended Unemployment Coverage (EUC) program. Interestingly, during the mid-70s and early 80s recessions, there was comparatively little increase in unemployment coverage, and the large Beveridge curve shifts were not caused by large movements in λ_t^{UI} and λ_t^{IU}. In contrast, a large increase in unemployment insurance coverage in the early-90s recession coincided with unusually large increases in $d\ln u_t^{UI}$ and $d\ln u_t^{IU}$ given the magnitude of the recession.[12] Second, λ^{IU} increased proportionally more for prime age women than it did for men, perhaps because of the added worker effect.[13] Finally, Figure 10 shows that older workers experienced a dramatic increase in λ^{IU}. This could be due to the nature of the recession as older workers had to come out of retirement because of large losses in stock market wealth. Note also that this increase is part of an upward trend going back to the mid-90s.

6 What drives movements in the unemployment rate?

In this section, we combine the results from the two previous sections to provide a fuller and more precise decomposition of unemployment rate movements than presented in Section 3. Our decomposition has 3 main components: (i) changes due to labor demand, (ii) changes due to labor supply, and (iii) changes due to matching efficiency. Labor demand includes movements along the Beveridge curve, shifts in the Beveridge curve due to layoffs and the

[12]Note that after its initial increase at the beginning of the 1991 recession, $d\ln u_t^{IU}$ remained at a high level for two years after the end of the recession, preventing the Beveridge curve to shift back more rapidly and unemployment to decline faster.

[13]See Sahin, Song and Hobijn (2009).

effect of demographics on the layoff rate. Labor supply consists of quits, movements in and out of the labor force, and the effect of demographics. Finally, movements in matching efficiency include changes in the composition of the unemployment pool (by demographics and reason for unemployment) and unexplained changes that appear to affect the match efficiency of all workers.

We first present our theoretical decomposition and then discuss the empirical results in light of historical movements and the current recession.

6.1 A decomposition of the unemployment rate

From Section 5, movements in the unemployment rate can be decomposed as

$$d\ln u_t^{ss} = d\ln u_t^{shifts} - \alpha^{UE} d\ln \lambda_t^{UE} + \eta_t \tag{28}$$

with $d\ln u_t^{shifts}$ given by (27). To separate movements along the Beveridge curve from changes in matching efficiency and movements in λ_t^{UE} due to composition, we proceed as in Section 4 and estimate a matching function on $\tilde{\lambda}_t^{UE} = \sum_{i=1}^{N} \sum_{j\in\{p,t,q\}} \omega_t \frac{u_t^{j,ss}}{u^{ss}} \lambda_{it}^{jE}$. Similarly to 3, we denote $\hat{\lambda}_t^{UE} = m_0 \left(\frac{v_t}{u_t^{ss,bc}}\right)^{1-\sigma}$ the job finding rate predicted by a stable matching function, where $u_t^{ss,bc}$ is the steady-state unemployment rate implied by a stable Beveridge curve that holds unemployment composition constant. Formally, $u_t^{ss,bc}$ satisfies

$$u_t^{ss,bc} = \frac{\tilde{s}_t}{\tilde{s}_t + \tilde{\lambda}_t^{UI}\tilde{\lambda}_t^{IE} + \left(\tilde{\lambda}_t^{IU} + \tilde{\lambda}_t^{IE}\right) m0 \left(\frac{v_t}{u_t^{ss,bc}}\right)^{1-\sigma}}$$

where $\tilde{s}_t = \tilde{\lambda}_t^{EI}\tilde{\lambda}_t^{IU} + \tilde{\lambda}_t^{IE}\tilde{\lambda}_t^{EU} + \tilde{\lambda}_t^{IU}\tilde{\lambda}_t^{EU}$. We then define $d\varepsilon_t = \ln \lambda_t^{UE} - \ln \hat{\lambda}_t^{UE}$.

Combining (23) with (28), we obtain our theoretical decomposition:

$$d\ln u_t^{ss} = d\ln u_t^{L^s} + d\ln u_t^{L^d} + d\ln u_t^{eff} + \eta_t \tag{29}$$

where

$$\begin{cases} d\ln u_t^{L^s} = d\ln u_t^{L^s shifts} + d\ln u_t^{L^s shifts,comp} \\ d\ln u_t^{L^d} = d\ln u_t^{bc} + d\ln u_t^{L^d shifts} + d\ln u_t^{L^d shifts,comp} \\ \text{with} \qquad d\ln u_t^{bc} = -\alpha^{UE} d\ln \hat{\lambda}_t^{UE} \\ d\ln u_t^{eff} = -\alpha^{UE} d\varepsilon_t - \alpha^{UE}\left(d\ln \lambda_t^{UE,reason} + d\ln \lambda_t^{UE,demog}\right) \end{cases} \tag{30}$$

6.2 Results

Table 7 presents the results of a variance decomposition using (29) and shows that labor demand accounts for almost 60 percent of unemployment fluctuations while labor supply movements account for about 30 percent. However, the two forces play very different roles at high and low frequencies. Movements along the Beveridge curve play almost no role at low frequencies as labor supply changes account for 84 percent for unemployment's trend since 1976. In contrast, the situation is reversed at business cycle frequencies.

To visualize these results, Figure 13 plots our decomposition of unemployment into labor demand, labor supply and changes in matching efficiency. For clarity of exposition, and similarly to Figure 2, the decomposition is plotted relative to a base year. Since 1969 is not available, we use 2000Q3, a time during which the three components were close to their 1976-2009 historical lows. In addition, Figure 14 plots the decomposition of each component into its subcomponents, following (30).

In a typical recession, a reduction in labor demand causes a movement down the Beveridge curve and an outward shift in the curve due to an increase in layoffs. In contrast, labor supply movements contribute little to cyclical movements in unemployment but are responsible for the trend in unemployment as labor demand movements. As we saw in the previous section, demographics explains a sizeable fraction of the trend in the labor supply while stronger attachment of women to the labor force account for the change in behavior.

Turning to changes in matching efficiency, composition (demographics or reason for unemployment) plays almost no role until the mid 90s. Thereafter however, reason for unemployment explains an increasing fraction of matching efficiency movements. This is due to the increasing contribution of permanent layoffs to total layoffs at the expense of temporary layoffs. As a result, a third of the lower than usual matching efficiency since 2001 can be accounted for by the larger share of unemployed workers on permanent layoffs. As we saw in Section 4 using micro data, the fact that unemployed workers are disproportionately concentrated in states with above average unemployment rates leads to further decline in matching efficiency.

Compared to historical averages, the 2008-2009 recessions is characterized by a stronger contribution of labor demand. Labor demand accounted for 2/3 of the unemployment rate in end 2009 while labor supply accounted for only 1/6. This 1/4 ratio is considerably lower than the $\simeq 1/2$ ratio suggested by Table 7. This result is likely due to the fact that, in the current recession and unlike in the mid-80s, the contribution of labor supply is mainly cyclical. This hypothesis is in line with the rapidity of the shift in the Beveridge curve since 2007 and suggests that the shift is more likely to reverse over the course of the business cycle.

7 Conclusion

to be written.

Appendix

Analytical expressions for three labor market states

To find the steady-state unemployment rate u_{it}^{ss}, employment rate e_{it}^{ss} and inactivity rate i_{it}^{ss} of each demographic group i, note that $\left\{U_{it}^{j}\right\}_{j\in\{p,t,q,o\}}$, U_{it}, E_{it} and U_{it} satisfy the system of differential equations (21) so that $\left\{U_{it}^{ss,j}\right\}_{j\in\{p,t,q,o\}}$, U_{it}^{ss}, E_{it}^{ss} and I_{it}^{ss} are the solutions of the system

$$\begin{cases} \sum_{j\in\{p,t,q,o\}} U_{it}^{ss,j}\lambda_{it}^{jE} + \lambda_{it}^{IE} I_{it} = (\sum_{j\in\{p,t,q\}} \lambda_{it}^{Ej} + \lambda_{it}^{EI})E_{it} \\ \lambda_{it}^{EI} E_{it} + \sum_{j\in\{p,t,q,o\}} U_{it}^{ss,j}\lambda_{it}^{jI} = (\lambda_{it}^{IE} + \lambda_{it}^{Io})I_{it} \\ U_{it}^{ss,j} = \frac{\lambda^{Ej}}{\lambda^{jE}+\lambda^{jI}} E_{it}^{ss}, \qquad \forall\ j \in \{p,t,q\} \\ U_{it}^{ss,o} = \frac{\lambda^{Io}}{\lambda^{oE}+\lambda^{oI}} I_{it}^{ss} \\ U_{it}^{ss} = \sum_{j\in\{p,t,q,o\}} U_{it}^{ss,j} \end{cases}$$

The steady-state unemployment rate u_{it}^{ss} is then obtained from $u_{it}^{ss} = \frac{U_{it}^{ss}}{LF_{it}}$ and satisfies

$$u_{it}^{ss} \equiv \frac{s_{it}}{s_{it} + f_{it}}$$

with s_{it} and f_{it} defined by

$$\begin{cases} s_t = \lambda_{it}^{EI}\lambda_{it}^{IU} + \lambda_{it}^{IE}\lambda_{it}^{EU} + \lambda_{it}^{IU}\lambda_{it}^{EU} \\ f_{it} = \lambda_{it}^{UI}\lambda_{it}^{IE} + \lambda_{it}^{IU}\lambda_{it}^{UE} + \lambda_{it}^{IE}\lambda_{it}^{UE} \end{cases}$$

and where the transition rates are given by

$$\begin{cases} \lambda_{it}^{UE} = \sum_{j\in\{p,t,q,o\}} \frac{u_{it}^{ss,j}}{u_{it}^{ss}}\lambda_{it}^{jE} \\ \lambda_{it}^{UI} = \sum_{j\in\{p,t,q,o\}} \frac{u_{it}^{ss,j}}{u_{it}^{ss}}\lambda_{it}^{jI} \\ \lambda_{it}^{EU} = \sum_{j\in\{p,t,q\}} \lambda_{it}^{Ej} \\ \lambda_{it}^{IU} = \lambda_{it}^{Io} \end{cases}$$

where $u_{it}^{ss} = \frac{U_{it}^{ss}}{LF_{it}}$, $u_{it}^{ss,j} = \frac{U_{it}^{ss,j}}{LF_{it}}$.

Log-linearizing (25), we can decompose hazard rate movements into changes caused by movements in each subgroup's hazard rate and into changes due to a composition effect (reason or demographic) from

$$
\begin{cases}
d\ln\lambda_t^{UB} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{u_i^{j,ss}}{u}\frac{\lambda_i^{jB}}{\lambda^{UB}} d\ln\lambda_{it}^{jB} + \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \frac{u^{j,ss}}{u^{ss}}\frac{\lambda^{jB}}{\lambda^{UB}} d\ln\frac{u_t^{j,ss}}{u_t^{ss}} + \sum_{i=1}^{N}\omega_i\frac{u_i^{ss}}{u^{ss}}\frac{\lambda_i^{UB}}{\lambda^{UB}} d\ln\omega_{it}\frac{u_{it}^{ss}}{u_t^{ss}} \\
\quad = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{u_i^{j,ss}}{u}\frac{\lambda_i^{jB}}{\lambda^{UB}} d\ln\lambda_{it}^{jB} + d\ln\lambda_t^{UB,reason} + d\ln\lambda_t^{UB,demog}, \qquad B\in\{E,I\}
\end{cases}
$$

$$
\begin{cases}
d\ln\lambda_t^{EU} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{e_i^{ss}}{e^{ss}}\frac{\lambda_i^{Ej}}{\lambda^{EU}} d\ln\lambda_{it}^{Ej} + \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{e_i^{ss}}{e^{ss}}\frac{\lambda_i^{Ej}}{\lambda^{EU}} d\ln\omega_{it}\frac{e_{it}^{ss}}{e_t^{ss}} \\
\quad = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{e_i^{ss}}{e^{ss}}\frac{\lambda_i^{Ej}}{\lambda^{EU}} d\ln\lambda_{it}^{Ej} + d\ln\lambda_t^{EU,demog}
\end{cases}
$$

$$
\begin{cases}
d\ln\lambda_t^{EI} = \sum_{i=1}^{N}\omega_i \frac{e_i^{ss}}{e^{ss}}\frac{\lambda_i^{EI}}{\lambda^{EI}} d\ln\lambda_{it}^{EI} + \sum_{i=1}^{N}\omega_i \frac{e_i^{ss}}{e^{ss}}\frac{\lambda_i^{EI}}{\lambda^{EI}} d\ln\omega_{it}\frac{e_{it}^{ss}}{e_t^{ss}} \\
\quad = \sum_{i=1}^{N}\omega_i \frac{e_i^{ss}}{e^{ss}}\frac{\lambda_i^{EI}}{\lambda^{EI}} d\ln\lambda_{it}^{EI} + d\ln\lambda_t^{EI,demog}
\end{cases}
$$

$$
\begin{cases}
d\ln\lambda_t^{IB} = \sum_{i=1}^{N}\omega_i \frac{i_i^{ss}}{i^{ss}}\frac{\lambda_i^{IB}}{\lambda^{IB}} d\ln\lambda_{it}^{IB} + \sum_{i=1}^{N}\omega_i \frac{i_i^{ss}}{i^{ss}}\frac{\lambda_i^{IB}}{\lambda^{IB}} d\ln\omega_{it}\frac{i_{it}^{ss}}{i_t^{ss}} \\
\quad = \sum_{i=1}^{N}\omega_i \frac{i_i^{ss}}{i^{ss}}\frac{\lambda_i^{IB}}{\lambda^{IB}} d\ln\lambda_{it}^{IB} + d\ln\lambda_t^{IB,demog}
\end{cases}
\qquad B\in\{E,U\}
$$

where the aggregate hazard rates $\tilde{\lambda}_t^{AB}$ that hold composition (by demographics and unemployment reason) constant are defined by

$$
\begin{cases}
\tilde{\lambda}_t^{UB} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{u_i^{j,ss}}{u^{ss}}\lambda_{it}^{jB}\ , \qquad B\in\{E,I\} \\
\tilde{\lambda}_t^{EU} = \sum_{i=1}^{N}\sum_{j\in\{p,t,q\}} \omega_i \frac{e_i^{ss}}{e^{ss}}\lambda_{it}^{Ej} \text{ and } \tilde{\lambda}_t^{EI} = \sum_{i=1}^{N}\omega_i\frac{e_i^{ss}}{e^{ss}}\lambda_{it}^{EI} \\
\tilde{\lambda}_t^{IU} = \sum_{i=1}^{N}\omega_i \frac{i_i^{ss}}{i^{ss}}\lambda_{it}^{Io} \text{ and } \tilde{\lambda}_t^{IE} = \sum_{i=1}^{N}\omega_i\frac{i_i^{ss}}{i^{ss}}\lambda_{it}^{EI}
\end{cases}
$$

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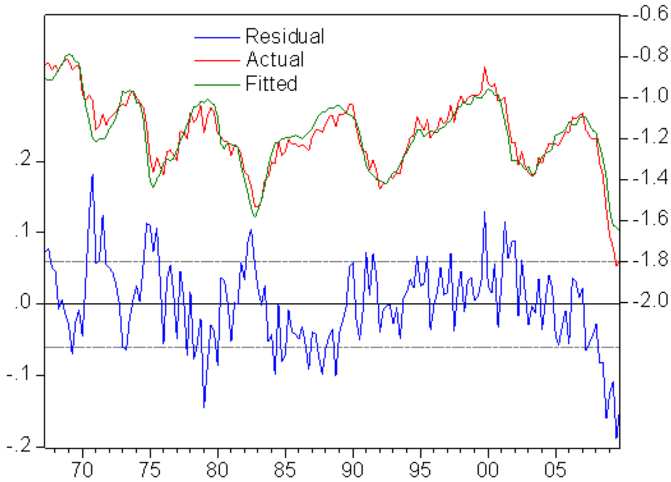

Figure 1: Empirical job finding rate, model job finding rate and residual, 1967-2009.

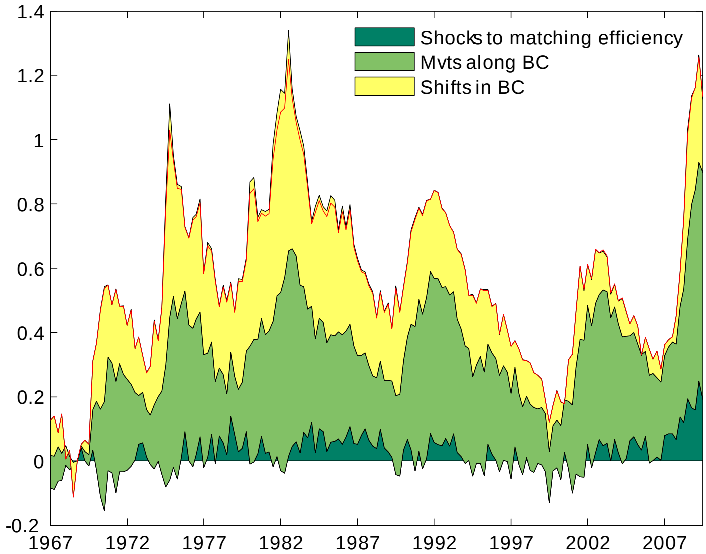

Figure 2: Decomposition of unemployment fluctuations (in logs) in the Beveridge curve space over 1967-2009. The colored areas sum to the approximated steady-state unemployment. The red line is the exact value of steady-state unemployment.

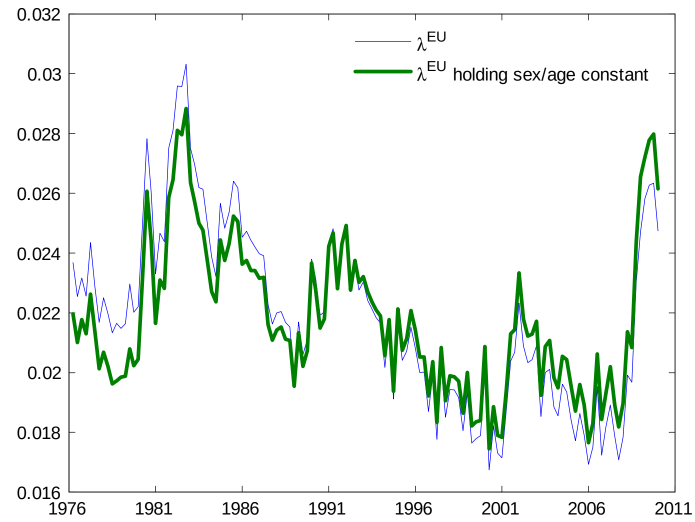

Figure 3: The effect of controlling for demographics on the job separation rate.

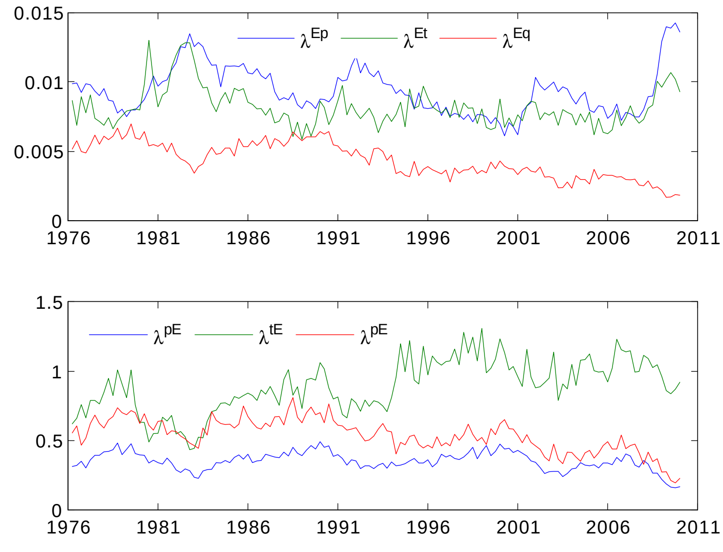

Figure 4: Unemployment inflow rate (upper panel) and unemployment outflow rate (lower panel) for job losers on permanent layoff, job losers on temporary layoff and job leavers.

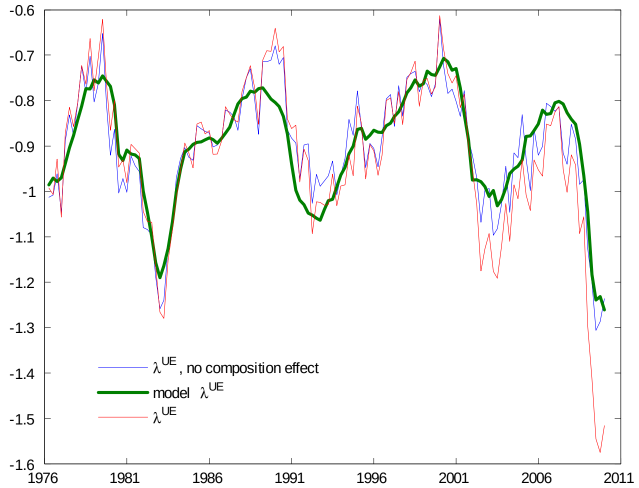

Figure 5: Actual job finding rate, job finding rate holding the share of each unemployment by reason constant (at its mean) and model job finding rate, 1976-2009.

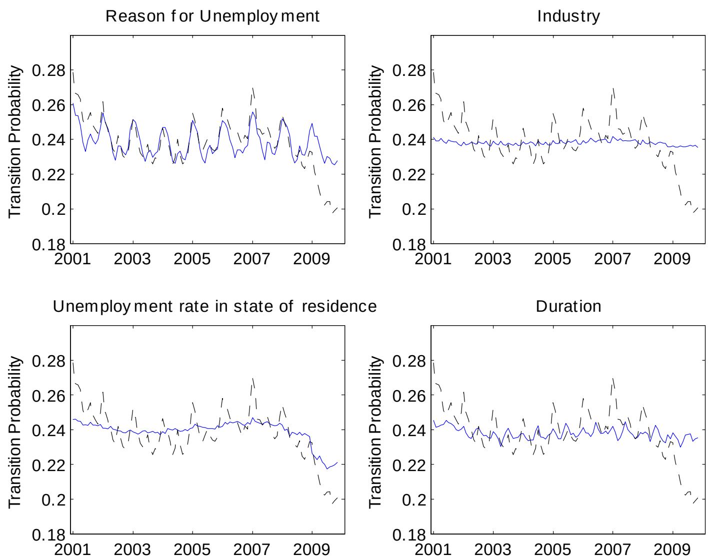

Figure 6: Contributions of unemployment composition to changes in unemployment exit probability using JOLTS data, 2001-2009. Each solid line represents the composition effect due to a particular characteristic, and dashed lines represent the total composition effect.

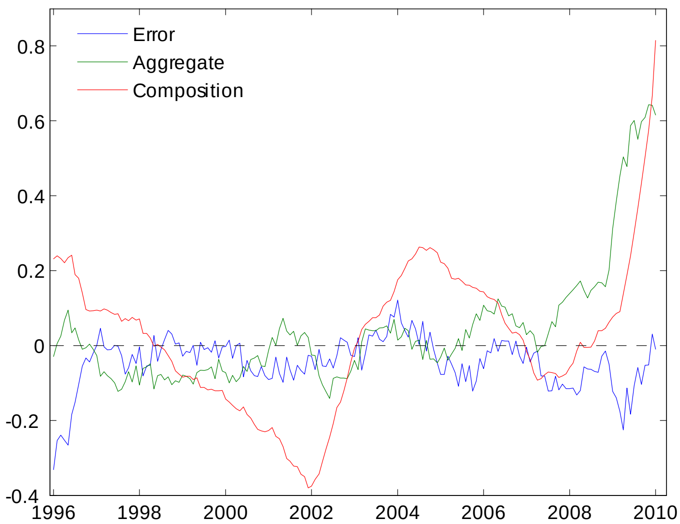

Figure 7: Decomposition of changes in matching efficiency into a composition effect, an unexplained aggregate effect and an error term capturing the difference between adjusted and unadjusted flows data, 1994-2009.

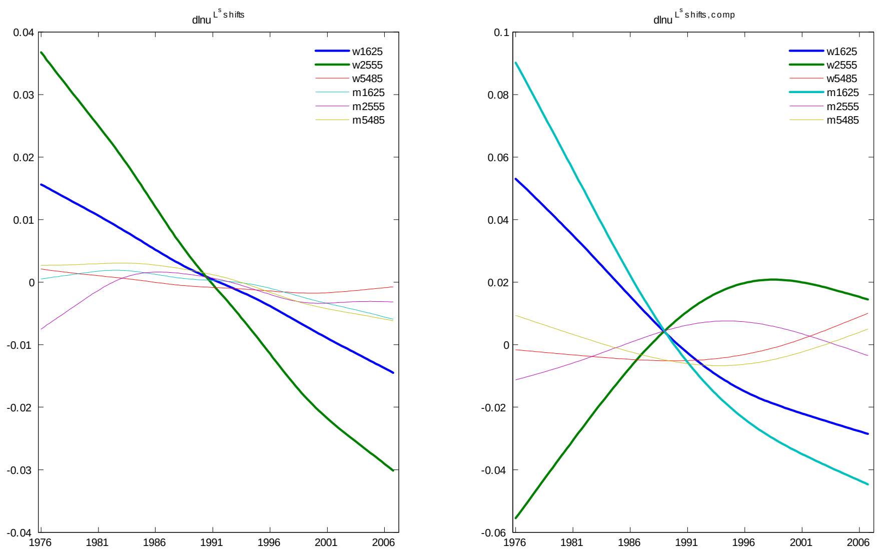

Figure 8: HP-filter trends ($\lambda = 10^5$) in Beveridge curve shifts due to changes in labor supply or to changes in demographics, 1976-2009.

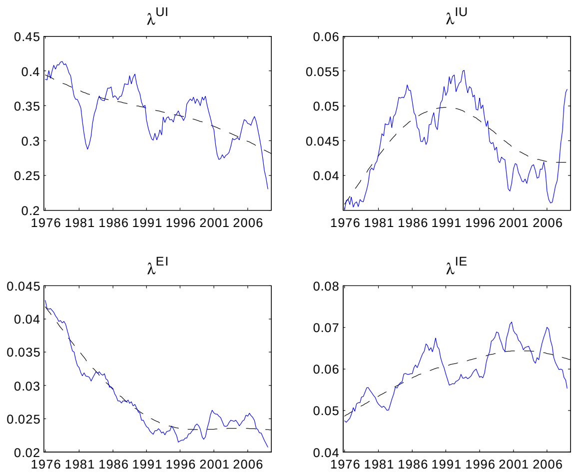

Figure 9: Transition rates for in-and-out of the labor force movements for women aged 25-55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

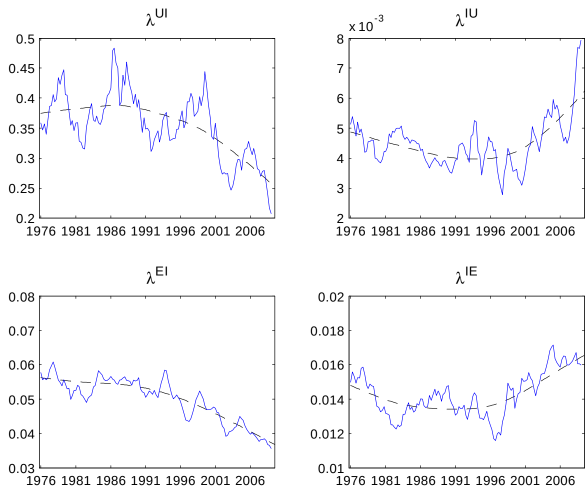

Figure 10: Transition rates for in-and-out of the labor force movements for women aged over 55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

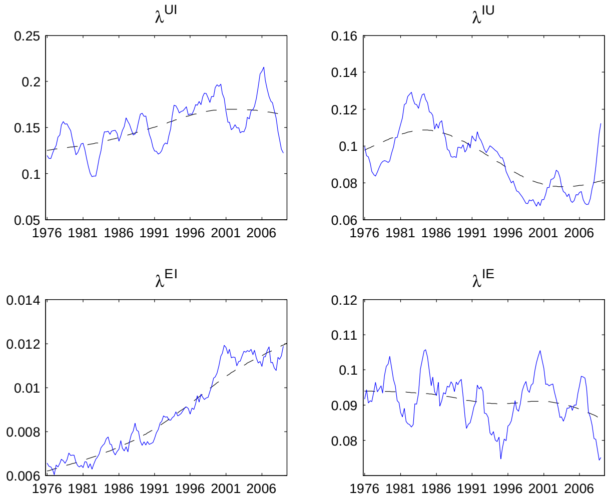

Figure 11: Transition rates for in-and-out of the labor force movements for men aged 25-55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

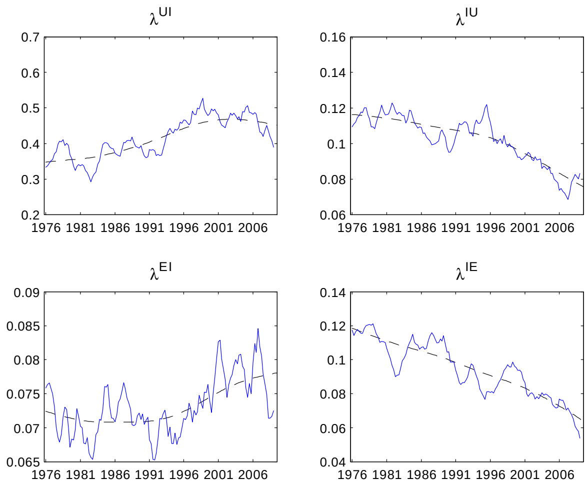

Figure 12: Transition rates for in-and-out of the labor force movements for men aged 16-25, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

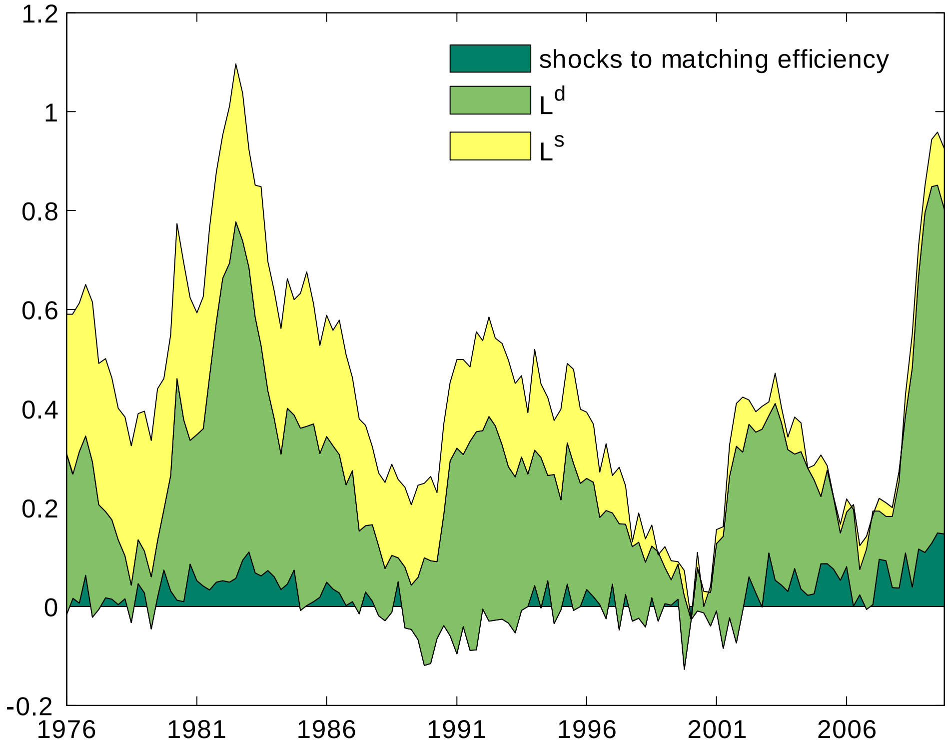

Figure 13: Decomposition of unemployment fluctuations (in logs) into labor demand movements, labor supply movements and shocks to matching efficiency over 1976-2009. The colored areas sum to the approximated steady-state unemployment.

Figure 14: Upper panel: decomposition of labor demand movements due to Beveridge curve movements, Beveridge curve shifts from permanent layoffs or temporary layoffs and the composition effect of demographics on the layoff rate. Middle panel: decomposition of labor supply movements due to Beveridge curve shifts caused by quits or individuals moving in and out of the labor force and to demographics. Lower panel: decomposition of changes in matching efficiency due to shocks to the matching function, composition of the unemployment pool by reason of unemployment and composition of the unemployment pool by demographics. 1976-2009.

Table 1: Estimating a Cobb-Douglas matching function

Dependent variable:	λ^{UE}	λ^{UE}	λ^{UE}	λ^{UE}	$\tilde{\lambda}^{UE}$
Sample (quarterly frequency)	1967-2006	1967-2006	1967-2009	2003-2009	1976-2006
Regression Estimation	(1) OLS	(2) GMM	(3) OLS	(4) OLS	(5) OLS
σ	0.64*** (0.01)	0.62*** (0.01)	0.62*** (0.01)	0.49*** (0.02)	0.68 (0.01)
R^2	0.89	--	0.89	0.95	0.80

Note: Standard-errors are reported in parentheses. In equation (2), I use 3 lags of v and u as instruments. I allow for first-order serial correlation in the residual.

Table 2: Variance decomposition of steady-state unemployment, 1967:Q2-2009:Q4

	Movements along the Beveridge curve	Shifts in the Beveridge curve	Shocks to the matching function
Raw data	0.48	0.42	0.10
Trend component	0.38	0.62	--
Cyclical component	0.60	0.40	--

Note: Trend component denotes the trend from an HP-filter (10^5) and cyclical component the deviation of the raw data from that trend.

Table 3. Estimating Hazards with Aggregated and Micro Data

	2001-2007 JOLTS		1994-2007 Comp. HWI UE Hazard		1976-2007 Comp. HWI	
	Micro	Agg.	Micro	Agg.	Micro	Agg.
Constant	0.326	0.326 (0.013)	0.236	0.266 (0.003)		
Elasticity	0.702 (0.015)	0.704 (.050)	0.706 (0.010)	0.71 (0.030)		

Note. Standard errors are in parentheses. Agg. estimates use weighted nonlinear least squares.

Table 6: Variance decomposition of Beveridge curve shifts, 1976:Q1-2009:Q4

	L^d	$L^{d,comp}$	L^s	$L^{s,comp}$
Raw data	0.35	0.10	0.36	0.20
Trend component	0.05	0.18	0.49	0.28
Cyclical component	0.65	0.00	0.25	0.10

Note: Trend component denotes the trend from an HP-filter (10^5) and cyclical component the deviation of the raw data from that trend.

Table 7: Variance decomposition of steady-state unemployment, 1976:Q1-2009:Q4

	Changes in L^d	Changes in L^s	Shocks to the matching function
Raw data	0.59	0.31	0.10
Trend component	0.16	0.84	--
Cyclical component	0.68	0.19	0.13

Note: Trend component denotes the trend from an HP-filter (10^5) and cyclical component the deviation of the raw data from that trend.

Table 4. Estimated Coefficients: Individual data (UE transition probability)

Explanatory Variable	Estimated Coefficient (expressed as odds ratio)			
	2001-2007 JOLTS	1994-2007 Comp. HWI	1976-2007 Comp. HWI	
			Pre 1994	Post 1994
Matching Function parameter				
Elasticity	0.817	0.783		
	(0.019)	(0.011)		
Other parameters				
Age	0.9933	0.9927		
	(0.0005)	(0.0003)		
Age squared	0.99987	0.99987		
	(0.00002)	(0.00002)		
Male dummy	1.111	1.107		
	(0.012)	(0.009)		
Permanent layoff dummy	0.706	0.708		
	(0.013)	(0.01)		
Temporary layoff dummy	2.056	1.947		
	(0.041)	(0.027)		
Temporary job ended dummy	0.944	0.932		
	(0.021)	(0.015)		
Reentrant dummy	0.743	0.723		
	(0.013)	(0.009)		
New Entrant dummy	0.418	0.400		
	(0.012)	(0.008)		
State unemployment rate (differenced from aggregate unemployment rate)	0.922	0.912		
	(0.005)	(0.003)		
Industry vacancy rate (differenced from aggregate vacancy rate)	1.028			
	(0.006)			
Unemployment duration	0.975	0.978		
	(0.002)	(0.0016)		
Duration interacted with average duration	1.0006	1.0004		
	(0.0001)	(0.00009)		
Pseudo R^2	0.0542	0.0543		

Note. Explanatory variables also include monthly dummies. All variables are significant at conventional levels of significance. Standard errors are in parentheses. Odds ratios are relative to age 30, female, job quitter with an unemployment spell of 0 weeks from an industry with the vacancy rate equal to the national vacancy rate and residing in a state with an unemployment rate equal to the national unemployment rate.

Table 5. Estimated Coefficients: Individual data (EU transition probability)

Explanatory Variable	Estimated Coefficient (expressed as odds ratio)			
	2001-2007 JOLTS	1994-2007 Comp. HWI	1976-2007 Comp. HWI	
			Pre 1994	Post 1994
Layoff				
Age	0.94	0.95		
	(0.002)	(0.001)		
Age squared	1.0005	1.0004		
	(0.00003)	(0.00002)		
Male dummy	0.72	0.70		
	(0.008)	(0.006)		
Aggregate vacancy rate	0.27	0.23		
	(0.11)	(0.12)		
Squared aggregate vacancy	2.15	1.35		
rate	(0.70)	(0.20)		
Industry vacancy rate	0.76			
(deviation from aggregate)	(0.014)			
Squared industry vacancy	1.076			
rate	(0.014)			
(deviation from aggregate)				
Average industry vacancy	0.98			
rate	(0.014)			
Quit				
Age	0.91	0.90		
	(0.005)	(0.003)		
Age squared	1.0006	1.0006		
	(0.00007)	(0.00005)		
Male dummy	1.03	1.10		
	(0.03)	(0.02)		
Aggregate vacancy rate	1.60	3.27		
	(1.41)	(3.84)		
Squared aggregate vacancy	0.92	0.79		
rate	(0.69)	(0.26)		
Industry vacancy rate	1.09			
(deviation from aggregate)	(0.054)			
Squared industry vacancy	0.98			
rate	(0.013)			
(deviation from aggregate)				
Average industry vacancy	1.08			
rate	(0.035)			
Pseudo R^2	0.014	0.014		

Note. Standard errors are in parentheses. Odds ratios are relative to age 30, female, from an industry with the vacancy rate equal to the national vacancy rate, and the national vacancy rate equal to its average.