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What Drives Movements in the Unemployment Rate?

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What drives movements in the unemployment rate? A decomposition of the Beveridge curve.[*]

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Abstract

This paper presents a framework to interpret movements in the Beveridge curve and analyze unemployment fluctuations. We decompose the unemployment rate into three main components: (1) a component driven by changes in labor demand –movements along the Beveridge curve and shifts in the Beveridge curve due to layoffs– (2) a component driven by changes in labor supply – shifts in the Beveridge curve due to quits, movements in-and-out of the labor force and demographics– and (3) a component driven by changes in the efficiency of matching unemployed workers to jobs. We find that cyclical movements in unemployment are dominated by changes in labor demand, but that changes in labor supply due to movements in-and-out of the labor force also play an important role. Further, cyclical changes in labor demand lead cyclical changes in labor supply. Changes in matching efficiency generally play a small role but can decline substantially in recessions. At low-frequencies, labor demand displays no trend, and changes in labor supply explain virtually all of the secular trend in unemployment since 1976.

JEL classifications: J6, E24, E32

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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. The Beveridge curve captures the downward sloping relationship between the unemployment rate and the job vacancy rate and is widely used as an indicator of the state of the labor market. Movements along the Beveridge curve, i.e., changes in unemployment due to changes in vacancies, are typically interpreted as cyclical movements in labor demand. However, shifts in the Beveridge curve are difficult to interpret. While they are sometimes seen as indicating movements in the level of "equilibrium" or "structural" unemployment, they can in fact be caused by a number of diverse factors; changes in the intensity of layoffs and quits, changes in labor force participation, or changes in the efficiency of matching workers to jobs.

In this paper, we present a framework to isolate the different components of the Beveridge curve, and we use that framework to decompose unemployment rate movements into three categories: (1) firm-induced changes in unemployment, i.e. movements in labor demand, (2) worker-induced changes in unemployment, i.e. movements in labor supply, and (3) changes in the efficiency of matching unemployed workers to jobs.

The first contribution of this paper is to present a framework to rigorously study movements in the Beveridge curve. We accomplish our Beveridge curve decomposition by first isolating the inflows and outflows of unemployment, following Shimer (2007). Using an aggregate matching function tying vacancy posting and unemployment to transitions from unemployment into employment, we decompose the outflow component into a component driven by changes in vacancies, i.e. movements along a stable Beveridge curve, and a component driven by changes in the efficiency of matching workers to jobs. We interpret movements along a stable Beveridge curve as changes in labor demand. To interpret the inflows of unemployment, we use CPS micro data to distinguish movements in layoffs, i.e. changes in labor demand, from changes in demographics, quits or movements in-and-out of the labor force, i.e. changes in labor supply.

The second contribution of this paper is to provide a comprehensive decomposition of the unemployment rate covering all frequencies over 1976-2009. We find that labor demand and labor supply contribute approximately equally to unemployment's variance, but that these two forces play very different roles at different frequencies.

At business cycle frequencies, labor demand accounts for three quarters of unemployment's variance, a result in line with the approach taken by the search literature and the canonical Mortensen-Pissarides (1994) model to focus on vacancy posting and job separation when studying unemployment fluctuations. However, movements in-and-out of the labor force explain close to a quarter of unemployment's variance, a result at odds with the conventional wisdom that movements in-and-out of the labor force played little role at business cycle frequencies (see e.g. Hall, 2005, Shimer, 2007, and Elsby, Michaels and Solon, 2009). Finally, changes in matching efficiency play on average a small role but can decline substantially in recessions. For instance, in the 2008-2009 recession, lower matching efficiency added about $1\frac{1}{2}$ percentage points to the unemployment rate.

We also study the timing of the different forces moving the unemployment rate. At the beginning of a recession, the Beveridge curve shifts out because of an increase in temporary layoffs. A quarter later, unemployment moves along the Beveridge curve as firms adjust vacancies. The Beveridge curve also shifts out further because of an increase in permanent layoffs. Then, another quarter later, labor supply responds to the economic situation; the Beveridge curve shifts in slightly because quits decline but shifts out further as workers display a stronger attachment to the labor force. While only suggestive, this chain of events could indicate that labor supply responds to labor demand at cyclical frequencies.

At low frequencies, we find little evidence of any trend in labor demand. In contrast, unemployment's trend since 1976 can be entirely accounted for by secular 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 documented by Abraham and Shimer (2001). The secular leftward shift in the Beveridge curve since 1976 correlates with a decline in the time-series volatility of business growth rates since 1976 and a decline in the job destruction rate (Davis, Faberman, Haltiwanger, Jarmin and Miranda, 2010). Thus, our results suggest that an explanation of these phenomena lies with secular changes in labor supply rather than with secular changes in labor demand.

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.[1] We take this literature one step further by decomposing the labor market flows 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 to better identify causes of Beveridge curve shifts.

The next section lays the theoretical groundwork for our decomposition. Section 3 estimates an aggregate matching function and decomposes changes in the unemployment rate into changes in labor demand, changes in labor supply, and changes in the matching function. Section 4 discusses the implications of our results. Section 5 concludes.

2 A Beveridge curve decomposition

In this section, we present a method to quantitatively decompose movements in the Beveridge curve. We decompose unemployment fluctuations into three categories; changes in labor demand –movements along the Beveridge curve and shifts in the Beveridge curve due to layoffs–, changes in labor supply –shifts in the Beveridge curve due to quits and movements in and out of the labor force–, and changes in matching efficiency.

[1] See, e.g., Shimer (2007), Elsby, Michaels and Solon (2009), Fujita and Ramey (2009), Elsby, Hobijn and Sahin (2009).

2.1 Steady-state unemployment

Let U_t, E_t, and I_t denote the number of unemployed, employed and inactive (out of the labor force) individuals, respectively, at instant $t \in \mathbb{R}_+$. Letting λ_t^{AB} denote 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

$$\begin{cases} \dot{U}_t = \lambda_t^{EU} E_t + \lambda_t^{IU} I_t - (\lambda_t^{UE} + \lambda_t^{UI}) U_t \\ \dot{E}_t = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - (\lambda_t^{EU} + \lambda_t^{EI}) E_t \\ \dot{I}_t = \lambda_t^{EI} E_t + \lambda_t^{UI} U_t - (\lambda_t^{IE} + \lambda_t^{IU}) I_t \end{cases} \quad (1)$$

As first argued by Shimer (2007), the magnitudes of the 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 $u_t = \frac{U_t}{LF_t}$ is very well approximated by its steady-state value u_t^{ss} so that

$$u_t \simeq \frac{s_t}{s_t + f_t} \equiv u_t^{ss} \quad (2)$$

with s_t and f_t defined by[2]

$$\begin{cases} s_t = \lambda_t^{EU} + \frac{\lambda_t^{EI} \lambda_t^{IU}}{1 - \lambda_t^{II}} \\ f_t = \lambda_t^{UE} + \frac{\lambda_t^{UI} \lambda_t^{IE}}{1 - \lambda_t^{II}}. \end{cases}$$

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),

[2] Expression (2) generalizes the simpler two-states case without movements in-and-out of the labor force in which $u_t^{ss} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \lambda_t^{UE}}$. With movements in-and-out of the labor force, workers can transition between U and E either directly (U-E) or in two steps by first leaving the labor force (U-I) and then by finding a job directly from inactivity (I-U). f_t, the "U-E transition probability" that matters for steady-state unemployment rate is then a weighted average of λ_t^{UE} and $\lambda_t^{UI} \lambda_t^{IE}$, with weights of 1 and $\frac{1}{1 - \lambda_t^{II}}$, the average time that a worker going U->I->E spends transitioning through state I. s_t has a similar expression.

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

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

where ν_t allows the efficiency of matching workers to firms to vary over time.

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

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

with $\lambda_t^{UIE} = \frac{\lambda_t^{UI}\lambda_t^{IE}}{1-\lambda_t^{II}}$. 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, as illustrated in Figure 1, the Beveridge curve shifts because of layoffs, quits or movements in and out of the labor force, i.e. when s_t or λ_t^{UIE} moves.

However, while the matching function is remarkably successful at modeling the job finding rate, the relation $\lambda_t^{UE} = m_0\left(\frac{v_t}{u_t}\right)^{1-\sigma}$ 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 $u_t^{ss,bc}$ as 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

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

Denoting $\hat{\lambda}_t^{UE} = m_0 \left(\frac{v_t}{u_t^{ss,bc}} \right)^{1-\sigma}$ the job finding rate predicted by a stable matching function, we can rewrite (4) as

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

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.[3]

Log-linearizing (2) around the mean of the hazard rates gives us:[4]

$$\begin{aligned} d\ln u_t^{ss} &= \alpha^{EI} d\ln \lambda_t^{EI} + \alpha^{IU} d\ln \lambda_t^{IU} + \alpha^{EU} d\ln \lambda_t^{EU} \\ &\quad - \alpha^{IE} d\ln \lambda_t^{IE} - \alpha^{UI} d\ln \lambda_t^{UI} - \alpha^{UE} d\ln \lambda_t^{UE} + \eta_t \end{aligned} \tag{7}$$

with $\left\{\alpha^{AB}\right\}$ some positive constants depending on the mean of $\left\{\lambda_t^{AB}\right\}$.[5] In this context, we can decompose unemployment movements in a Beveridge curve framework from

$$d\ln u_t^{ss} = d\ln u_t^{bc} + d\ln u_t^{shifts} + d\ln u_t^{eff} + \eta_t \tag{8}$$

where $d\ln u_t^{bc} \equiv -\alpha^{UE} d\ln \hat{\lambda}_t^{UE} = -\alpha^{UE}(1-\sigma) d\ln \frac{v_t^{UE}}{u_t^{ss,bc}}$ represents movements along the Beveridge curve, $d\ln u_t^{eff} \equiv \alpha^{UE} d\varepsilon_t$ captures the shifts in the Beveridge curve caused by changes

[3]Note that ε_t is different from ν_t. While (3) is useful to highlight movements in matching efficiency, this regression conditions on actual unemployment, not the unemployment that would have prevailed had there been no changes in matching efficiency. To properly identify changes in matching efficiency, one needs to determine $u_t^{ss,bc}$; the unemployment rate implied by a stable matching function and the current levels of s_t and λ_t^{UIE}. Deviations of the actual job finding rate from the job finding rate implied by $u_t^{ss,bc}$ can then be interpreted as due to a change in matching efficiency.

[4]A first-order approximation is very good on average, but η_t can become non-negligible during episodes of high unemployment rate. Thus, for our quantitative exercises, we rely on a second-order approximation, which performs extremely well. The expressions for the second-order coefficients are shown in the Appendix.

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

in matching efficiency, and shifts in the Beveridge curve are given by

$$d\ln u_t^{shift} \equiv \alpha^{EU} d\ln \lambda_t^{EU} + \alpha^{EI} d\ln \lambda_t^{EI} + \alpha^{IU} d\ln \lambda_t^{IU} - \alpha^{IE} d\ln \lambda_t^{IE} - \alpha^{UI} d\ln \lambda_t^{UI}$$

Shifts in the Beveridge curve can occur through changes in workers' attachment to the labor force or through changes in the probability that workers separate from their job and join the unemployment pool, either through a layoff or through a quit. Finally, the residual term η_t corresponds to the approximation error.

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

$$Var\left(d\ln u_t^{ss}\right) = Cov(d\ln u_t^{ss}, d\ln u_t^{bc}) + Cov(d\ln u_t^{ss}, d\ln u_t^{shifts}) + Cov(d\ln u_t^{ss}, d\ln u_t^{eff}) + Cov(d\ln u_t^{ss}, \eta_t). \quad (9)$$

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.

2.4 Interpreting shifts in the Beveridge curve

The Beveridge curve can shift if the employment-unemployment transition probability changes. However, an employed worker can join the unemployment pool for two reasons: a layoff or a quit. While a layoff is a firm-induced movement in unemployment, a quit is a decision of the worker. Thus, from a conceptual point of view, it is important to distinguish these two concepts empirically. In addition, shifts in the Beveridge curve can occur through changes in workers' attachment to the labor force. Thus, to identify and interpret the different forces that can shift the Beveridge curve, we separate job leavers, job losers and labor force entrants, and 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.

Further, a number of researchers (e.g. Abraham and Shimer, 2001) emphasize that changes in demographics have been an important force behind the secular trend in unemployment. In particular, as the labor force gets older, the average turn-over rates declines, and the unemployment rate goes down. Thus, to better interpret the low-frequency shifts in the Beveridge curve, we extend our decomposition (8) and isolate the direct effect of demographics on unemployment.

Formally, for each demographic group $i \in \{1,..,N\}$, 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 $\{\lambda_i^{jE}, \lambda_i^{Ej}, \lambda_i^{jI}\}$, $j \in \{p,t,q\}$ and $\{\lambda_i^{oE}, \lambda_i^{Io}, \lambda_i^{oI}\}$.

In this case, the system of differential equations (1) satisfied by the number of unemployed U_{it}, employed E_{it} and inactive I_{it} in demographic group i becomes

$$\begin{cases} \dot{U}_{it}^j = \lambda_{it}^{Ej} E_{it} - (\lambda_{it}^{jE} + \lambda_{it}^{jI}) U_{it}^j, \quad j \in \{p,t,q\} \\ \dot{U}_{it}^o = \lambda_{it}^{Io} I_{it} - (\lambda_{it}^{oE} + \lambda_{it}^{oI}) U_{it}^o \\ \dot{E}_{it} = \lambda_{it}^{pE} U_{it}^p + \lambda_{it}^{tE} U_{it}^t + \lambda_{it}^{qE} U_{it}^q + \lambda_{it}^{oE} U_{it}^o + \lambda_{it}^{IE} I_{it} - (\lambda_{it}^{El} + \lambda_{it}^{Eq} + \lambda_{it}^{EI}) E_{it} \\ \dot{I}_{it} = \lambda_{it}^{EI} E_{it} + \lambda_{it}^{oI} U_{it}^o - (\lambda_{it}^{IE} + \lambda_{it}^{Io}) I_{it} \end{cases} \tag{10}$$

With $U_t = \sum_{i=1}^{N} \left(U_{it}^p + U_{it}^t + U_{it}^q + U_{it}^o \right)$, the aggregate steady-state unemployment rate u_t^{ss} satisfies (2) with the average transition rates given by

$$\begin{cases} \lambda_t^{UB} = \sum_{i=1}^{N} \sum_{j \in \{p,t,q,o\}} \frac{U_{it}^j}{U_t} \lambda_{it}^{jB}, \quad B \in \{E, I\} \\ \lambda_t^{EU} = \sum_{i=1}^{N} \sum_{j \in \{p,t,q\}} \frac{E_{it}}{E_t} \lambda_{it}^{Ej} \text{ and } \lambda_t^{EI} = \sum_{i=1}^{N} \frac{E_{it}}{E_t} \lambda_{it}^{EI} \\ \lambda_t^{IU} = \sum_{i=1}^{N} \frac{I_{it}}{I_t} \lambda_{it}^{Io} \text{ and } \lambda_t^{IE} = \sum_{i=1}^{N} \frac{I_{it}}{I_t} \lambda_{it}^{IE} \end{cases} \tag{11}$$

Using the steady-state approximations, we can approximate (11) with

$$\begin{cases} \lambda_t^{UB} \simeq \sum_{i=1}^{N} \sum_{j\in\{p,t,q,o\}} \omega_{it} \frac{u_{it}^{j,ss}}{u_t^{ss}} \lambda_{it}^{jB}, \quad B \in \{E, I\} \\ \lambda_t^{EU} \simeq \sum_{i=1}^{N} \sum_{j\in\{p,t,q\}} \omega_{it} \frac{e_{it}^{ss}}{e_t^{ss}} \lambda_{it}^{Ej} \text{ and } \lambda_t^{EI} \simeq \sum_{i=1}^{N} \omega_{it} \frac{e_{it}^{ss}}{e_t^{ss}} \lambda_{it}^{EI} \\ \lambda_t^{IU} \simeq \sum_{i=1}^{N} \omega_{it} \frac{i_{it}^{ss}}{i_t^{ss}} \lambda_{it}^{Io} \text{ and } \lambda_t^{IE} \simeq \sum_{i=1}^{N} \omega_{it} \frac{i_{it}^{ss}}{i_t^{ss}} \lambda_{it}^{IE} \end{cases} \tag{12}$$

where $\omega_{it} = \frac{LF_{it}}{LF_t}$ is the share of group i in the labor force and u_{it}^{ss}, e_{it}^{ss} and i_{it}^{ss} denote respectively the steady-state unemployment rate, employment rate and inactivity rate of group i. The steady-state unemployment rate for category i satisfies $u_{it}^{ss} = \frac{s_{it}}{s_{it}+f_{it}}$ since the system of differential equations (10) holds independently for each demographic group.[6]

To isolate the direct effect of demographics, we log-linearize (12) and get for λ_t^{EU}

$$d\ln\lambda_t^{EU} = \sum_{i=1}^{N} \omega_i \frac{e_i^{ss}}{e^{ss}} \frac{\lambda_i^{EU}}{\lambda^{EU}} \left(d\ln\lambda_{it}^{EU} + d\ln\left(\omega_{it}\frac{e_{it}^{ss}}{e_t^{ss}}\right)\right) = d\ln\tilde{\lambda}_t^{EU} + d\ln\lambda_t^{EU,demog} \tag{13}$$

and similarly for the other transition rates.[7] The first term corresponds to movements in $\tilde{\lambda}_t^{EU} \equiv \sum_{i=1}^{N} \omega_i \frac{e_i^{ss}}{e^{ss}} \lambda_{it}^{EU}$, the hazard rate that holds the share of each demographic group constant. The second term, $d\ln\lambda_t^{EU,demog} \equiv \sum_{i=1}^{N} \omega_i \frac{e_i^{ss}}{e^{ss}} \frac{\lambda_i^{EU}}{\lambda^{EU}} d\ln\omega_{it}\frac{e_{it}^{ss}}{e_t^{ss}}$, corresponds 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 employment pool ($\frac{e_i^{ss}}{e^{ss}}$).

Finally, to separate quits from layoffs, note that $\lambda_t^{EU} = \sum_{j\in\{p,t,q\}} \lambda_t^{Ej}$ and $\lambda_t^{Ej} = \sum_{i=1}^{N} \omega_{it} \frac{e_{it}^{ss}}{e_t^{ss}} \lambda_{it}^{Ej}$, $\forall j \in \{p,t,q\}$.

[6] See the Appendix for more details.

[7] See the Appendix for expressions of the other transition rates. Further, throughout the paper, we present the derivations to a first-order for clarity of exposition, but we use a second-order approximation for the quantitative results. For instance, for λ^{EU}, we took a second-order expansion of $\ln\lambda_t^{EU}$ in (12), and we split the contributions of the cross-order terms in half between each two components.

2.5 A labor demand/labor supply decomposition

We can now rewrite (8) to isolate the contribution of demographics and separate layoffs from quits and movements in-and-out of the labor force:

$$d\ln u_t^{ss} = \underbrace{d\ln u_t^{bc} + d\ln u_t^{shifts,layoffs}}_{L^d} + \underbrace{d\ln u_t^{shifts,quits} + d\ln u_t^{shifts,LF-NLF} + d\ln u_t^{demog}}_{L^s} + d\ln u_t^{eff} + \eta_t. \tag{14}$$

where[8]

$$\begin{cases} d\ln u_t^{bc} = -\alpha^{UE} d\ln \hat{\lambda}_t^{UE} \\ d\ln u_t^{shifts,layoffs} = \alpha^{EU}\left(d\ln \tilde{\lambda}_t^{Ep} + d\ln \tilde{\lambda}_t^{Et}\right) \text{ and } d\ln u_t^{shifts,quits} = \alpha^{EU} d\ln \tilde{\lambda}_t^{Eq} \\ d\ln u_t^{shifts,LF-NLF} = \alpha^{EI} d\ln \tilde{\lambda}_t^{EI} + \alpha^{IU} d\ln \tilde{\lambda}_t^{IU} - \alpha^{IE} d\ln \tilde{\lambda}_t^{IE} - \alpha^{UI} d\ln \tilde{\lambda}_t^{UI} \\ d\ln u_t^{demog} = \alpha^{EI} d\ln \lambda_t^{EI,demog} + \alpha^{IU} d\ln \lambda_t^{IU,demog} + \alpha^{EU} d\ln \lambda_t^{Eq,demog} \\ \qquad -\alpha^{IE} d\ln \lambda_t^{IE,demog} - \alpha^{UI} d\ln \lambda_t^{UI,demog} \\ d\ln u_t^{eff} = -\alpha^{UE} d\varepsilon_t - \alpha^{UE} d\ln \lambda_t^{UE,demog}. \end{cases}$$

We group the firms' induced movements in unemployment (due to vacancies or layoffs) under the heading "labor demand" and the workers' induced movements in unemployment (due to quits, movements in and out of the labor force and changes in demographics) under the heading "labor supply". Importantly, we do not presume that labor demand and labor supply are independent forces as changes in one factor could influence the other. Rather, we think of the labor demand/labor supply classification as a useful framework to think about the mechanisms (changes in firms' behavior or changes in workers' behavior) at play behind unemployment fluctuations.

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

3 Empirical results

3.1 Measuring individuals' transition rates

To identify the individuals' 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. We classify jobless workers according to the event that led to their unemployment status: a permanent layoff, a temporary layoff, a quit and a labor force entrance.[9] Further, we 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.

For each demographic group, there are 6 possible states with $S = \{U^p, U^t, U^q, U^o, E, I\}$. To account for time aggregation bias, we consider a continuous environment in which data are available at discrete dates t and proceed in a similar fashion to 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:[10]

$$\dot{n}_t^{AB}(\tau) = \sum_{C \neq B} n_t^{AC}(\tau)\lambda_t^{CB} - n_t^{AB}(\tau) \sum_{C \neq B} \lambda_t^{BC}, \qquad \forall\ A \neq B. \tag{15}$$

We then solve this system of differential equations numerically to obtain the transition rates for each demographic group. We use data from the CPS from January 1976 through December 2009 and calculate the quarterly series for the transition rates over 1976Q1-2009Q4 by averaging the monthly series. Finally, we adjust the transition rates for the 94 CPS redesign as described in the Appendix.

[9] To address Shimer's (2007) worry that the quit/layoff distinction may be hard to interpret in the CPS because a sizeable fraction of households who report being a job leaver in month t subsequently report being a job loser at $t+1$, we discarded the observations with "impossible" transitions (such as job leaver to job loser).

[10] Because an unemployed worker cannot change reason for unemployment or because a job loser/leaver cannot be a labor force entrant, some transitions are forbidden, and we impose $\lambda_t^{AB} = 0$ for such transitions (for example, $\lambda^{pq} = 0$, $\lambda^{Ip} = 0$, etc..)

3.2 Estimating a matching function

We estimate a matching function by regressing

$$\ln \lambda_t^{UE} = (1-\sigma) \ln \frac{v_t}{u_t} + m_0 + \nu_t \tag{16}$$

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

We estimate (16) with monthly data using the composite help-wanted index presented in Barnichon (2010) as a measure of vacancy posting.[11] 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. The elasticity σ is precisely estimated at 0.62, 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 (16) may be subject to an endogeneity bias. We then estimate (16) 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 0.60. Figure 2 plots the residual of equation (16) estimated over 1967-2009. While the matching function appears relatively stable over time, a testimony of the success of the matching function, the residual can become large, as in the third quarter of 2009.

3.3 A decomposition of unemployment fluctuations

3.3.1 Aggregate decomposition

In this section, we use (14) to decompose unemployment fluctuations into: (i) movements due to changes in labor demand, (ii) movements due to changes in labor supply, and (iii) changes

[11] This composite index uses the print help-wanted index until 1994 to proxy for vacancy posting. Although Abraham (1987) argued that the print help-wanted index is distorted by various changes in the labor and newspaper markets, Zagorsky (1998) later argued that the print help-wanted index is not significantly biased until 1994. After 1994, the composite index controls for the emergence of online advertising (at the expense of print advertising) by combining information from the Conference Board print and online help-wanted advertising indexes with the BLS Job Openings and Labor Turnover Survey (JOLTS). See Barnichon (2010) for more details.

in matching efficiency.

To better visualize the contribution of each category in history, we log-linearize unemployment around the base date 2000q3.[12] That base date is attractive because it corresponds to the highest reading for vacancy posting per capita as well as the lowest value for $\ln u_t^{shift}$.[13] Figure 3 plots (log) unemployment and its components relative to their 2000q3 values. To express the y-axis in units of unemployment rate, we use a logarithmic scale.

Figure 3 suggests that both changes in labor demand and changes in labor supply contribute to unemployment's fluctuations. However, the secular trend in unemployment appears to originate in changes in labor supply, while changes in labor demand appear to be mainly cyclical. A variance decomposition confirms this impression, and Table 2 shows that while labor demand and labor supply contribute to respectively 50 and 30 percent of unemployment's variance on average, movements in labor supply account for virtually all the trend in unemployment since 1976.[14] In contrast, changes in labor demand account for 82 percent of unemployment's cyclical fluctuations (excluding movements due to changes in matching efficiency). Nonetheless, the contribution of changes in labor supply at cyclical frequencies is far from negligible at 18 percent.

With a contribution of 13 percent, changes in matching efficiency 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 3 shows some marked decrease in matching efficiencies in the aftermath of the 82 peaks in unemployment and during the 2008-2009 recession. Without any loss in matching efficiency, Figure 3 shows that unemployment would have been about 50 basis points lower over 1984-1988 and about 150 basis points lower

[12] As previously mentioned, we use a second-order approximation (see the Appendix) to ensure that the approximation remains good. To classify the cross-order terms (in, say, labor demand versus labor supply), we split their contribution in half between each two components. The red line in Figure 3 plots the exact value of the steady-state unemployment rate, which is very close to our approximation.

[13] Thus, 2000q3 corresponds to the date with the most leftward Beveridge curve, and that base year can be used as a reference point from which we can quickly visualize the rise and fall in trend unemployment as well as the cyclical fluctuations over the last 35 years.

[14] To separate trend and cyclical unemployment, we decompose changes in unemployment into a trend component (from an HP-filter, $\lambda = 10^5$) and a cyclical component.

in 2009.[15]

3.3.2 Digging further

To better interpret changes in labor demand and changes in labor supply, we now study the behavior of their subcomponents.

Figure 4 and 5 plot the decomposition of labor demand and labor supply following (14). We can see that there is no clear trend in any of the components of unemployment due to labor demand. In contrast, labor supply seems responsible for the secular decline in unemployment since 1976. Table 3 presents the results of a variance decomposition using (14) and confirms this visual inspection. While movements along the Beveridge curve, layoffs and movements in-and-out of the labor force each account for about a third of unemployment's variance, the picture is very different when one considers high and low-frequency movements separately. Demographics and movements in-and out of the labor force are the prime driving forces of secular shifts in unemployment but labor demand (movements along the Beveridge curve and layoffs) is the main driving force at business cycle frequencies. We thus discuss each frequency range separately.

Business cycle fluctuations: As Table 3 shows, movements along the Beveridge curve and shifts due to layoffs are the two main determinants of unemployment fluctuations and account for respectively 37 and 46 percent of the cyclical fluctuations in unemployment. However, Table 3 shows that the cyclical contribution of movements in-and-out of the labor force is far from negligible at around 23 percent. Quits have a small but negative contribution of -7 percent, a result consistent with Elsby, Michaels and Solon's (2009) finding using unemployment duration data that quits to unemployment move countercyclically.

To better interpret these results, Table 4 presents the correlation matrix for the main determinants of unemployment fluctuations at business cycle frequencies. Shifts in the Beveridge

[15] In a companion paper (Barnichon and Figura, 2010), we investigate the forces behind changes in matching efficiency.

curve due to layoffs and movements along the Beveridge curve are strongly positively correlated, in line with the usual assumption that they both respond to firms' labor demand. The correlation with shifts due to temporary layoffs is less strong, because, as we can see in Figure 4, firms' increasing reliance on permanent layoffs at the expense of temporary layoffs muted the cyclicality of temporary layoffs in the second-half of the sample. Shifts in the Beveridge curve due to movements in-and-out of the labor force are strongly positively correlated with shifts due to layoffs and to movements along the Beveridge curve.

As we can see in Figure 5, movements in-and-out of the labor force contribute to some of the rise in the unemployment rate in recessions. To visualize the role played by movements in-and-out of the labor force, Figures 6 to 9 plot the evolution of the four hazard rates related to movements in-and-out of inactivity for specific demographic groups. A general observation is that attachment to the labor force is countercyclical, with workers more likely to join/stay in the labor force during recessions. This is particularly true for prime-age females as shown in Figure 6.[16] Comparing prime-age women with prime-age men in Figures 6 and 7, the behavior of λ^{UI} and λ^{IU} shows that women's attachment to the labor force is more countercyclical than for men. This phenomenon may be a sign of the added worker effect, according to which women are more likely to join/remain in the labor force when their husband has lost his job.[17] Further, older workers can also experience strong cyclical movements in λ^{IU} (Figure 8).[18]

Finally, Table 5 reports the timing of the peak correlation between any two series and shows that changes in unemployment follow a particular chain of events. Temporary layoffs lead permanent layoffs and changes in job posting, which themselves lead quits and movements in-and-out of the labor force. Thus, at the beginning of a recession, the Beveridge curve shifts out because temporary layoffs increase. A quarter later, unemployment moves along the

[16] This could be due to the extension of unemployment benefits duration during recessions. In fact, during the mid-70s and early 80s recessions, the increases in unemployment coverage were smaller, and the large increases in unemployment 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.

[17] See Sahin, Song and Hobijn (2009) for a discussion of the added-worker effect in the 2008-2009 recession.

[18] This is particularly true in the 2008-2009 recession (especially women) and 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.

Beveridge curve as firms adjust vacancies and the Beveridge curve shifts out further because of more permanent layoffs. Then, another quarter later, labor supply responds to the economic situation; the Beveridge curve shifts in slightly because quits decline but also shifts out further as workers show a stronger attachment to the labor force. While only suggestive, this chain event could indicate that labor supply responds to labor demand at cyclical frequencies.

Low-frequency movements: Shimer (1998, 2001) and Abraham and Shimer (2001) identified two forces that could be responsible for the low-frequency movements in unemployment since 1976: the aging of the baby boom and the increase in women's labor force participation rate. Consistent with this result, Figure 5 shows that the trend in labor supply originates in demographics and movements in-and-out of the labor force. Table 4 confirms this idea quantitatively and shows that the two forces can explain virtually all of the trend in unemployment. To explore this result in more details, we now look at the behavior of specific demographics groups since 1976.

The right panel of Figure 10 plots the trends in $d\ln u_t^{demog}$ 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. At the same time, another demographic change had an opposite effect on unemployment. The increase in the share of prime age female inside the labor force until the mid-90s dampened the baby boom's effect as women historically had a lower job finding rate and higher job separation rate than men.

The left panel of Figure 10 plots the trends in $d\ln u_t^{shifts,LF-NLF}$ for six demographic groups and highlights a downward trend in unemployment caused by a change in the behavior of women. Consistent with Abraham and Shimer's (2001) finding that women's labor-market-participation decisions have converged towards those of men, Figure 6 shows two changes in prime age women transition rates over 1976-2009.[19] First, the secular increase in λ^{IU} until the

[19] Abraham and Shimer (2001) also documented these two changes using annual transition probabilities.

mid-90s and the secular increase in λ^{IE} show that women were getting increasingly likely to join 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 remain in the unemployment pool after an employment spell rather than drop out of the labor force.

As shown in Figure 5, quits to unemployment present little evidence of a trend, except perhaps in the last 10-15 years. This trend can be traced back to a secular decline in the rate of quits to unemployment amongst men and women aged 16 to 35.[20]

Looking forward, two more recent labor supply trends are worth mentioning. First, Figure 8 plots the transition rates for men and women aged over 55. A trend apparent since the late 90s is that older workers are increasingly likely to join the labor force as λ^{IU} and λ^{IE} are following upward trends.[21] We can also notice an increase in labor force attachment as both λ^{UI} and λ^{EI} are following downward trends. Second, Figure 9 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. Using (14), we can infer the consequence of such trends in terms of steady-state unemployment. Because of the larger demographic weight of older workers, their positive contribution would dominate the negative contribution of younger workers, and the unemployment rate would increase slightly. Extrapolating the trend in labor force participation behavior since 2000 for young and old workers implies a steady-state unemployment rate about a quarter of a percentage point higher in 2015.[22]

[20]The other demographic groups present little evidence of a trend. See also Duca and Campbell (2007). While our evidence only pertains to quits to unemployment, it is likely that a similar secular decline occurred for all quits as Fallick and Fleischman (2004) and Rogerson and Shimer (2010) also report a secular decline in job-to-job transitions since 1994.

[21]This is especially true for women.

[22]Formally, we extrapolated the trend growth rates in labor force participation (λ^{IU}, λ^{UI} ,λ^{EI} and λ^{IE}) for young and old workers over 2010-2016 using the 2000-2007 average growth rate of the HP-filter trends.

4 Theoretical implications

Business cycle fluctuations: At business cycle frequencies, our results can be summarized as follows: (i) movements along the Beveridge curve and job separation (layoffs and quits) account for a large share (76 percent) but not all of unemployment's variance, (ii) movements in-and-out of the labor force account for a quarter of unemployment's variance and lag movements in layoffs and vacancy posting by a quarter, (iii) quits are procyclical and lag layoffs by a quarter, (iv) changes in matching efficiency are generally small but can at times account for significant changes in the unemployment rate.

The Mortensen-Pissarides (1994) search and matching model has become the canonical model of equilibrium unemployment. In that model, and consistent with (i), unemployment fluctuations are driven by changes in job posting and job separation. However, considering (ii), 25 percent of unemployment fluctuations remains unaccounted for. This result is surprising given the conventional wisdom that movements in-and-out of the labor force played little role at business cycle frequencies (see e.g. Hall, 2005, Shimer, 2005, 2007 and Elsby, Michaels and Solon, 2009). Thus, introducing a labor force participation decision in the model is an important avenue for future research (see Garibaldi and Wasmer, 2005 and Haefke and Reiter, 2006 for efforts in that direction). In addition, accounting for movements in-and-out of the labor force would help explain some of the unemployment volatility puzzle.[23]

Moreover, in the MP model, quits and layoffs are indistinguishable since a match terminates when it is jointly optimal for both parties to separate. However, in the data, quits and layoffs display very different time series properties: quits are negatively correlated with layoffs, and quits lag layoffs by one quarter.

Finally, while shocks to matching efficiency are rarely considered in search models, (iv) suggests that they may be a useful addition to the set of shocks considered to explain unemployment fluctuations.

[23] The unemployment volatility puzzle is the fact that the standard MP model cannot replicate the volatility of unemployment given productivity shocks of plausible magnitude (Shimer, 2005).

Low-frequency movements: At low-frequencies, our main finding is the absence of any significant trend in labor demand and the fact that movements in labor supply account for all of the trend in unemployment. This result suggests that any explanation of the trend in unemployment since 1976 lies with demographics and changes in workers behavior rather than with any direct changes in firms' labor demand. Davis, Faberman, Haltiwanger, Jarmin and Miranda (2010) link the secular decline in the job destruction rate to the secular decline in the unemployment inflow rate. Since we can attribute all of the latter to demographics and behavioral changes in labor supply (in particular, a stronger attachment of women to the labor force), our evidence suggests that the secular decline in job destruction is related to changes in labor supply rather than to changes in labor demand.[24]

Davis, Haltiwanger, Jarmin and Miranda (2007) also document a decline in cross-sectional dispersion of business growth rates and in the time-series volatility of business growth rates since 1976. Again, the absence of a trend in labor demand suggests that labor supply may have played an important role here. For example, since older workers have longer tenures and have a lower turn-over rate than young workers, some of the decline in business growth rate volatility may be due to the aging of the baby boom. In contrast, any labor demand based explanation (such as a decline in the variance of idiosyncratic shocks hitting firms) must also justify the absence of any significant trend in labor demand (such as why the layoff rate did not decline).

5 Conclusion

This paper presents a framework to interpret movements in the Beveridge curve and decompose the components of unemployment fluctuations. We find that movements in labor demand are the main determinants of cyclical fluctuations in unemployment but that movements in-and-out of the labor force play an important role and account for almost a quarter of unemployment's

[24] Of course, stronger attachment of workers to the labor force could in turn have been triggered by labor demand changes such as increased economic uncertainty. However, the fact that we find no trend in labor demand suggests a less direct link.

variance. Further, labor demand leads labor supply, possibly indicating a causal interpretation as workers are more likely to join/stay in the labor force during recessions. Possible explanations include wealth effects and the added-worker effect for spouses. At low-frequencies, labor demand appears to play no direct role. Unemployment's trend since 1976 can be entirely accounted for by secular 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. Finally, while changes in matching efficiency generally play a small role, they can decline substantially in recessions. For instance, in the 2008-2009 recession, lower matching efficiency added about $1\frac{1}{2}$ percentage points to the unemployment rate. In a companion paper (Barnichon and Figura, 2010), we explore the possible mechanisms behind such large changes in matching efficiency.

Appendix

Steady-state values for the 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 (1) 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

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

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

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

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

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

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

Isolating the direct effect of demographics

We can isolate the direct effect of demographics by log-linearizing (12) so that

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

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

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

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

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

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

A second-order decomposition

A second-order Taylor expansion of

$$u_t^{ss} = \frac{s_t}{s_t + f_t}$$

with s_t and f_t defined by

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

gives us

$$\begin{aligned} d \ln u_t^{ss} \quad = \quad & -\alpha^{UI} \frac{d\lambda_t^{UI}}{\lambda^{UI}} + \frac{1}{2} \frac{\lambda^{IE^2}}{(s+f)^2} \left(\lambda_t^{UI} - \lambda^{UI}\right)^2 + \\ & -\alpha^{UE} \frac{d\lambda_t^{UE}}{\lambda^{UE}} + \frac{1}{2} \frac{\left(\lambda^{IU} + \lambda^{IE}\right)^2}{(s+f)^2} \left(\lambda_t^{UE} - \lambda^{UE}\right)^2 \\ & -\alpha^{IE} \frac{d\lambda_t^{IE}}{\lambda^{IE}} + \frac{1}{2} \left[-\frac{\lambda^{EU^2}}{s^2} + \frac{\left(\lambda^{EI} + \lambda^{UI} + \lambda^{UE}\right)^2}{(s+f)^2} \right] \left(\lambda_t^{IE} - \lambda^{IE}\right)^2 \\ & +\alpha^{EI} \frac{d\lambda_t^{EI}}{\lambda^{EI}} + \frac{1}{2} \left[-\frac{\lambda^{IU^2}}{s^2} + \frac{\lambda^{IU^2}}{(s+f)^2} \right] \left(\lambda_t^{EI} - \lambda^{EI}\right)^2 \\ & +\alpha^{EU} \frac{d\lambda_t^{EU}}{\lambda^{EU}} + \frac{1}{2} \left[-\frac{\left(\lambda^{IE} + \lambda^{IU}\right)^2}{s^2} + \frac{\left(\lambda^{IE} + \lambda^{IU}\right)^2}{(s+f)^2} \right] \left(\lambda_t^{EU} - \lambda^{EU}\right)^2 \\ & +\alpha^{IU} \frac{d\lambda_t^{IU}}{\lambda^{IU}} + \frac{1}{2} \left(\lambda^{EI} + \lambda^{EU}\right)^2 \left[-\frac{\left(\lambda^{EI} + \lambda^{EU}\right)^2}{s^2} + \frac{\left(\lambda^{EI} + \lambda^{EU} + \lambda^{UE}\right)^2}{(s+f)^2} \right] \left(\lambda_t^{IU} - \lambda^{IU}\right)^2 \\ & + \textit{cross-order terms} + \eta_t \end{aligned} \tag{17}$$

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

To classify the cross-order terms (in, say, labor demand versus labor supply), we split their contribution in half between each two components.

Finally, to separate movements along the Beveridge curve from changes in matching efficiency, note that $\varepsilon_t = \ln\lambda_t^{UE} - \ln\hat{\lambda}_t^{UE}$ with $\hat{\lambda}_t^{UE} = m_0\left(\frac{v_t}{u_t^{ss,bc}}\right)^{1-\sigma}$. To a second-order, we can write $d\varepsilon_t = \frac{d\lambda_t^{UE}}{\lambda^{UE}} - \frac{d\hat{\lambda}_t^{UE}}{\lambda^{UE}} - \left(\frac{d\lambda_t^{UE^2}}{\lambda^{UE^2}} - \frac{d\hat{\lambda}_t^{UE^2}}{\lambda^{UE^2}}\right)$, so that by defining $d\varepsilon_t^1 = \frac{d\lambda_t^{UE}}{\lambda^{UE}} - \frac{d\hat{\lambda}_t^{UE}}{\lambda^{UE}}$ and $d\varepsilon_t^2 = \frac{d\lambda_t^{UE^2}}{\lambda^{UE^2}} - \frac{d\hat{\lambda}_t^{UE^2}}{\lambda^{UE^2}}$, we can replace $d\lambda_t^{UE}$ and $d\left(\lambda_t^{UE}\right)^2$ in (17) using

$$\begin{aligned}\frac{d\lambda_t^{UE}}{\lambda^{UE}} &= \frac{d\hat{\lambda}_t^{UE}}{\lambda^{UE}} + d\varepsilon_t^1 \\ \frac{d\left(\lambda_t^{UE}\right)^2}{\lambda^{UE}} &= \frac{d\left(\hat{\lambda}_t^{UE}\right)^2}{\lambda^{UE}} + d\varepsilon_t^2\end{aligned}$$

Correction for the 1994 CPS redesign

As explained in Polivka and Miller (1998), the 1994 redesign of the CPS caused a discontinuity in the way workers were classified between permanent job losers (i.e. other job losers), temporary job losers (i.e. on layoffs), job leavers, reentrants to the labor force and new entrants to the labor force (although we do not distinguish between the last two categories). As a result, the transition probabilities display a discontinuity in the first month of 1994.

To "correct" the series for the redesign, we proceed as follows. We start from the monthly transition probabilities obtained from matched data for each demographic group. We remove the 94m1 value for each transition probability (since its value corresponds to the redesigned survey, not the pre-94 survey), and instead estimate a value consistent with the pre-94 survey. To do so, we use the transition probability average value over 1993m6-1993m12 (the monthly probabilities can be very noisy so we average them over 6 months to smooth them out)[25] that we multiply by the average growth rate of the transition probability over 1994m1-2009. That

[25] Taking a the average over 3-months or 12-months does not change the the result.

way, we capture the long-run trend in the transition probability. Over 1994m2-2009, we simply adjust the transition probability by the difference between the average of the original values over 94m1-94m6 (to control for the influence of noise or seasonality) and the inferred 94m1 value.

By eliminating the jumps in the transition probabilities in 1994m1, we are assuming that these discontinuities were solely caused by the CPS redesign. Thus, the validity of our approach rests on the fact that 1994m1 was not a month with large "true" movements in transition probabilities. We think that this is unlikely because there is no such large movements in the aggregate job finding rate and aggregate job separation rate obtained from duration data (Shimer, 2007 and Elsby, Michaels and Solon, 2009) that do not suffer from these discontinuities. (these authors treat the 1994 discontinuity by using data from the first and fifth rotation group, for which the unemployment duration measure (and thus their transition probability measures) was unaffected by the redesign. Moreover, Abraham and Shimer (2001) used independent data from the Census Employment Survey to evaluate the effect of the CPS redesign on the average transition probabilities from matched data. They found that only λ^{UI} and λ^{IU} were significantly affected, and that, after correction of these discontinuities (using the CES employment-population ratio), none of the transition probabilities displayed large movements in 1994.

Finally, we checked ex-post that our procedure had little effect on the stocks, i.e. on the measure of the aggregate unemployment rate and on the unemployment rate of each demographic group, consistent with Polivka and Miller's conclusion (1998) that the redesign did not affect the measure of unemployment.

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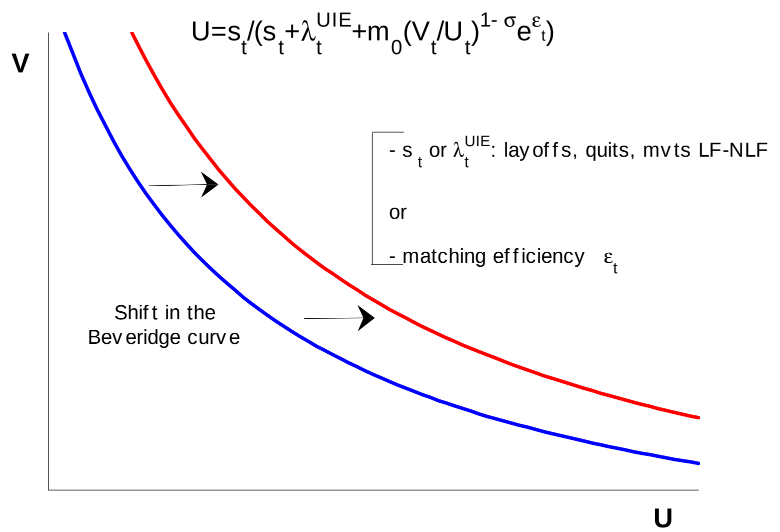

Figure 1: Shifts in the Beveridge curve.

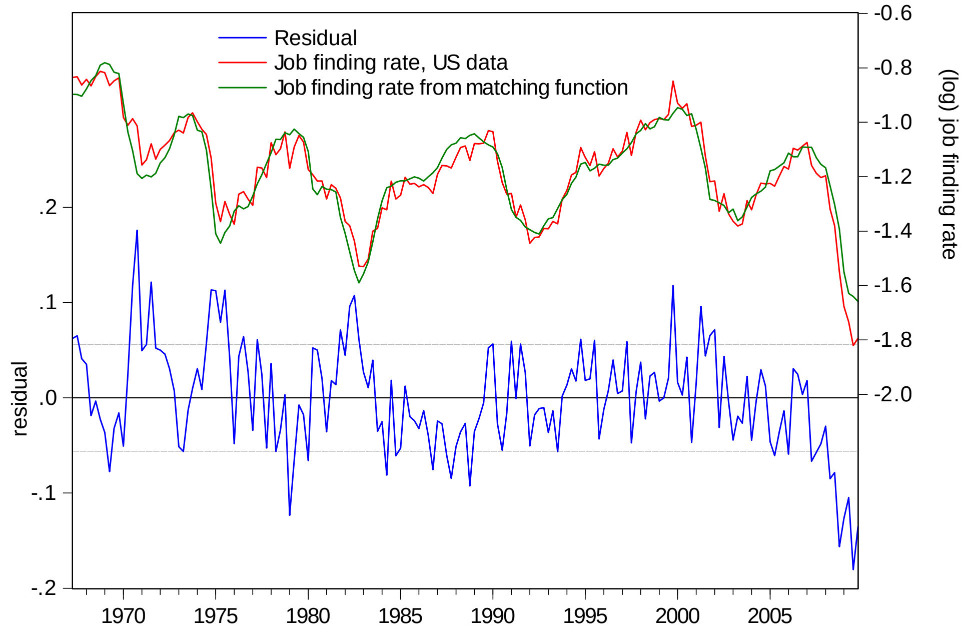

Figure 2: Empirical (log) job finding rate, model job finding rate and residual, 1967-2009.

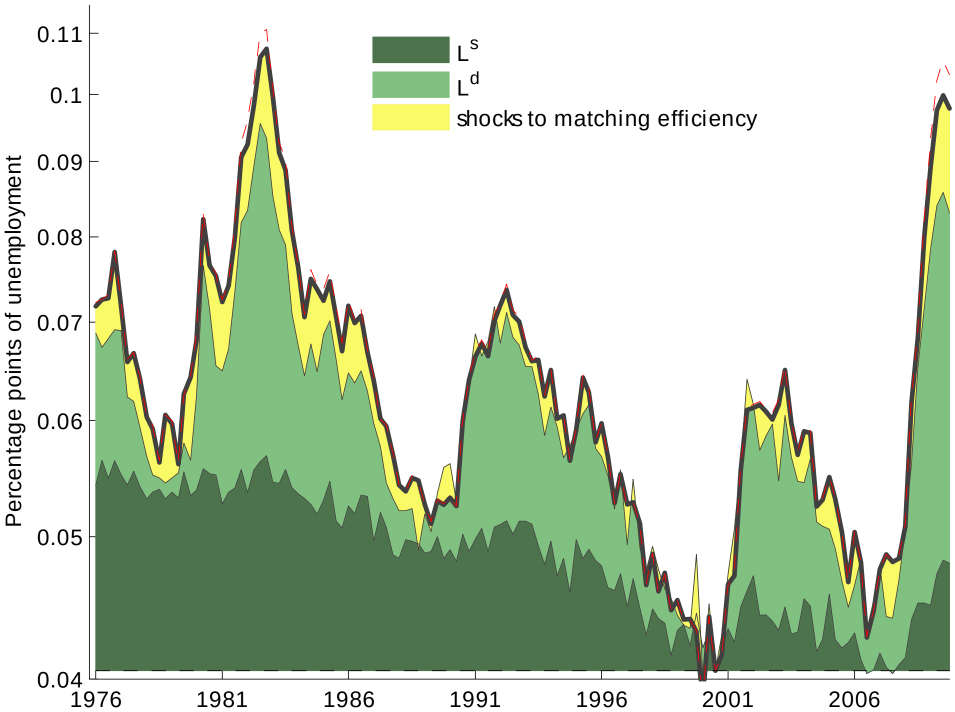

Figure 3: Decomposition of unemployment fluctuations into labor demand movements, labor supply movements and shocks to matching efficiency over 1976-2009. The y-axis uses a logarithmic scale. The decomposition uses 2000Q3 as the base year. The colored areas sum to the approximated steady-state unemployment. The dashed red line is the exact value of steady-state unemployment.

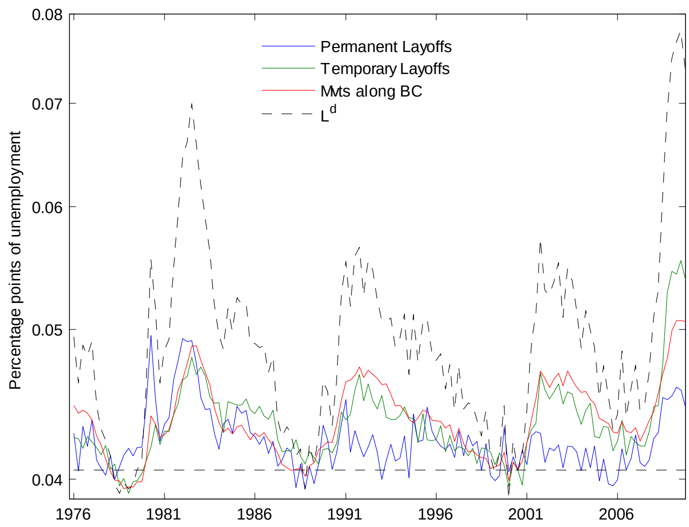

Figure 4: Decomposition of labor demand movements into movements along the Beveridge curve and Beveridge curve shifts from permanent layoffs or temporary layoffs, 1976-2009. The decomposition uses 2000Q3 as the base year. The y-axis uses a logarithmic scale.

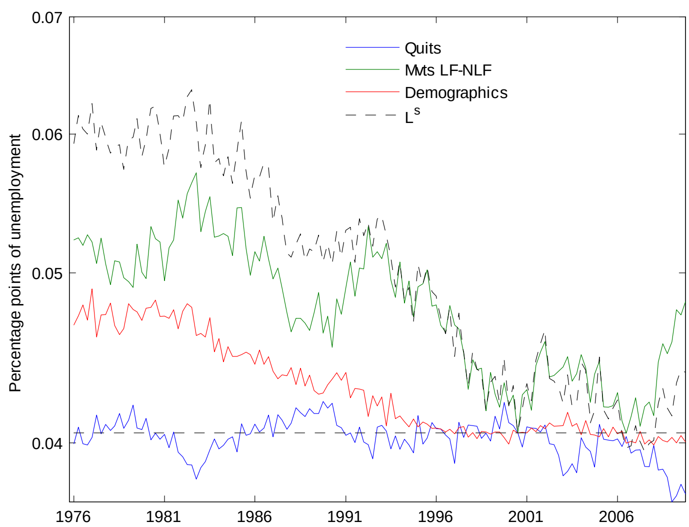

Figure 5: Decomposition of labor supply movements into Beveridge curve shifts due to quits, movements in-and-out of the labor force and demographics, 1976-2009. The decomposition uses 2000Q3 as the base year. The y-axis uses a logarithmic scale.

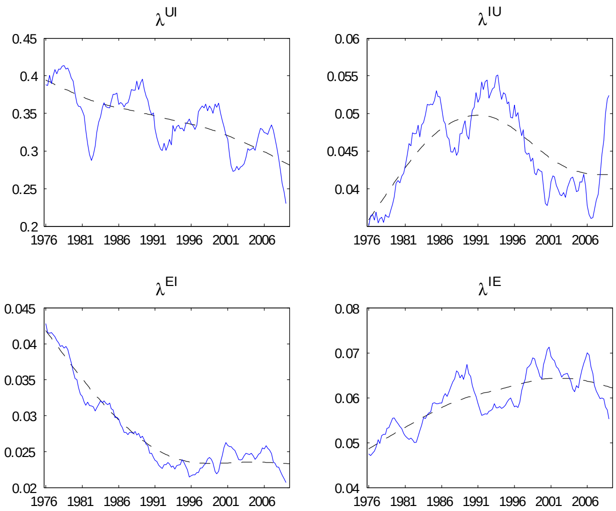

Figure 6: Transition rates for in-and-out of the labor force movements for women aged 25-55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

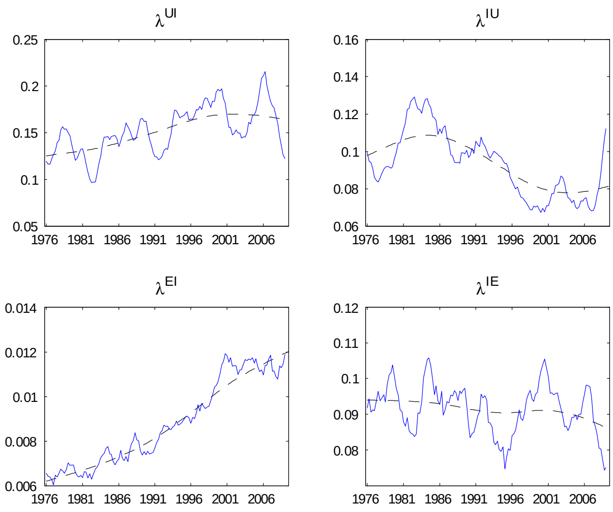

Figure 7: Transition rates for in-and-out of the labor force movements for men aged 25-55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

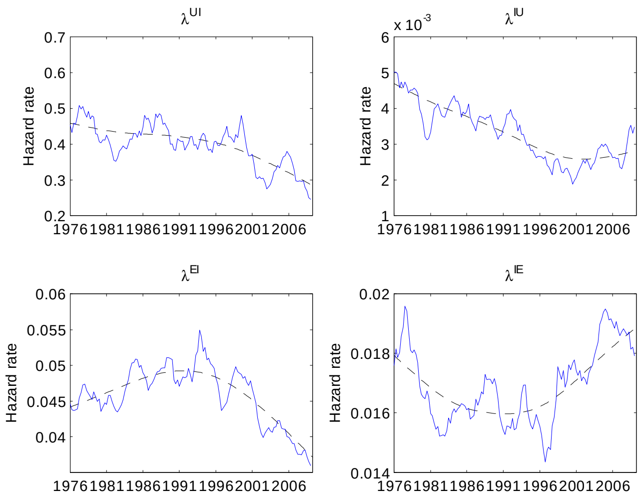

Figure 8: Transition rates for in-and-out of the labor force movements for men and women aged over 55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

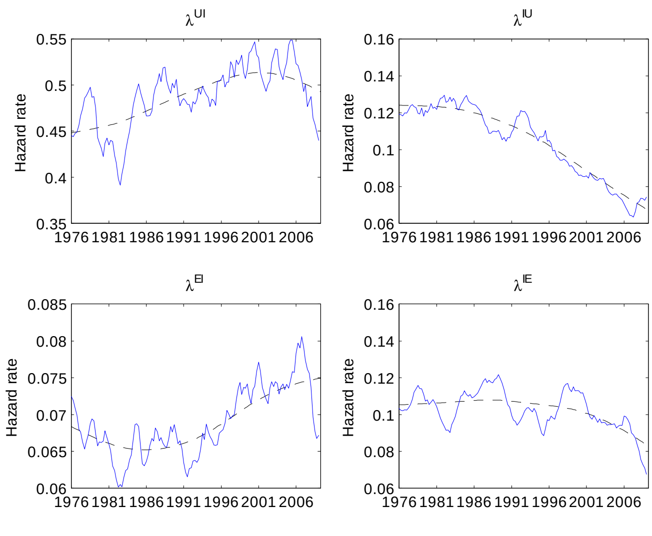

Figure 9: Transition rates for in-and-out of the labor force movements for men and women aged 16-25, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

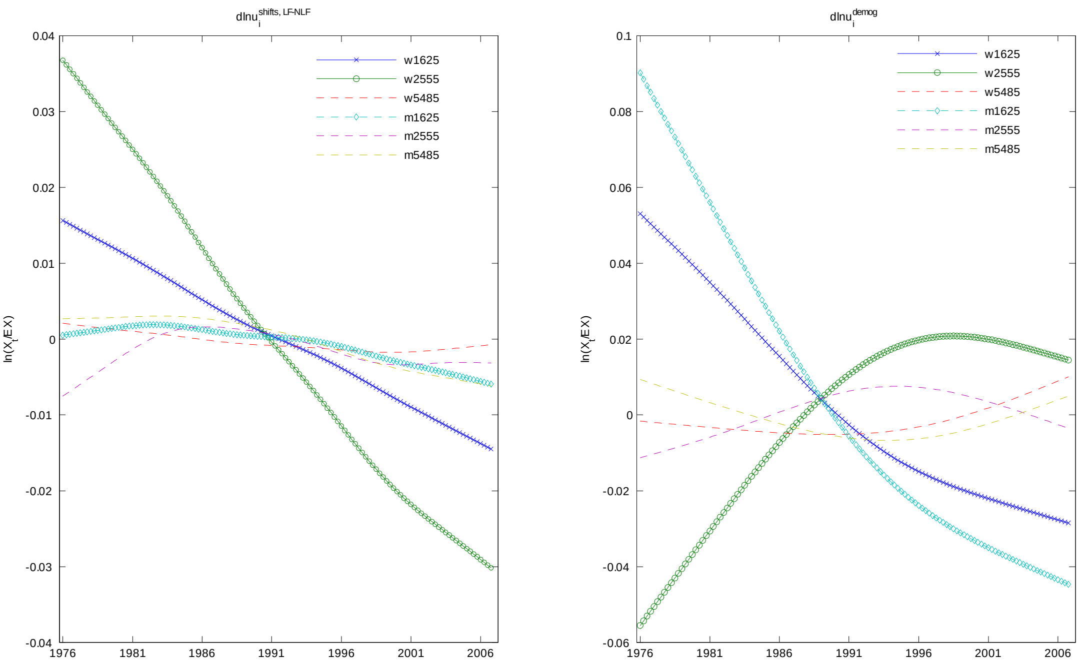

Figure 10: HP-filter trends ($\lambda = 10^5$) in Beveridge curve shifts due to changes in labor supply or to changes in demographics, 1976-2009. Left Panel: trends in unemployment due to movements in-and-out of the labor force ($d\ln u_{it}^{shifts,LF-NLF}$) by demographic group (women 16-24, women 25-55, women 54-85, men 16-24, men 25-55, men 54-85). Right Panel: trends in unemployment due to changes in the weight of each demographic group in the population ($d\ln u_{it}^{demog}$). All variables are expressed as log-deviations from their average values.

Table 1: Estimating a Cobb-Douglas matching function

Dependent variable:	λ^{UE}	λ^{UE}
Sample (quarterly frequency)	1967-2009	1967-2009
Regression	(1)	(2)
Estimation	OLS	GMM
σ	0.62*** (0.01)	0.61*** (0.01)
R^2	0.89	--

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

		Raw data	Trend component	Cyclical component
L^d	*Mvts along BC*	0.24	-0.13	0.37
	Layoffs	0.25	0.05	0.46
L^s	*Quits*	-0.04	0.06	-0.07
	Mvts LF-NLF	0.28	0.61	0.23
	Demographics	0.12	0.42	0.02
Matching efficiency		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. Mvts along BC refers to movements along the Beveridge curve and Mvts LF-NLF refers to movements in-and-out of the labor force.

Table 4: Correlation matrix of the determinants of cyclical unemployment, 1976-2009

	Temporary layoffs	*Permanent layoffs*	*Mvts along BC*	*Quits Mvts*	*LF-NLF*
Temporary layoffs	1	0.56	0.54	-0.52	0.42
Permanent layoffs	-	1	0.88	-0.65	0.71
Mvts along BC	-	-	1	-0.68	0.71
Quits	-	-	-	1	-0.62
Mvts LF-NLF	-	-	-	-	1

Note: All variables are detrended with an HP-filter (10^5).

Table 5: Lead-lag structure of the determinants of cyclical unemployment, 1976-2009

	Temporary layoffs	*Permanent layoffs*	*Mvts along BC*	*Quits Mvts*	*LF-NLF*
Temporary layoffs	0	1	1	2	2
Permanent layoffs	-	0	0	0	1
Mvts along BC	-	-	0	0	1
Quits	-	-	-	0	0
Mvts LF-NLF	-	-	-	-	0

Note: The table reports the value of *j* for which corr(X_t,Y_{t+j}) is highest (in absolute value).