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

Regis Barnichon
Federal Reserve Board

Andrew Figura
Federal Reserve Board

February 20, 2011

Abstract

This paper presents a framework to interpret movements in the Beveridge curve and analyze unemployment fluctuations. We decompose unemployment fluctuations 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, at business cycle frequencies, changes in labor demand lead changes in labor supply. While changes in matching efficiency are smaller, on average, than movements in labor demand or labor supply, matching efficiency can play a significant role during recessions. At low-frequencies, labor demand displays no trend, and the secular trend in unemployment since 1976 is driven by changes in labor supply.

*We would like to thank Alessia Campolmi, Shigeru Fujita, Bart Hobijn, Marianna Kudlyak, Chris Nekarda, Rob Valletta and seminar participants at the Chicago Fed, the CREI-CEPR Workshop on Changes in Labor Market Dynamics, the JOLTS Symposium at the BLS, the National Bank of Hungary, the New York Fed and the San Francisco Fed. The views expressed here do not necessarily reflect those of the Federal Reserve Board or of the Federal Reserve System. Any errors are our own.

JEL classifications: J6, E24, E32

Keywords: Unemployment fluctuations, Beveridge curve, Gross Worker Flows, Matching efficiency.

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 (Figure 1) 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, or labor demand driven, changes in unemployment, (2) worker-induced, or labor supply driven, changes in unemployment, 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, while changes in matching efficiency play on average a smaller role than changes in labor demand or labor supply, matching efficiency 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 over the business cycle. 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, labor demand displays no trend, and the trend in unemployment is driven by secular changes in labor supply, specifically the aging of the baby boom and the increasing attachment of women to the labor force. These two popular explanations (e.g., Perry 1970, Flaim 1979, Shimer 1998, 2001, and Abraham and Shimer, 2001) explain virtually all of the trend in unemployment. In contrast, another popular explanation –the decrease in men's labor force participation rate (Juhn, Murphy and Topel, 1991)– played a comparatively much smaller role.

Our results have a number of theoretical implications. At business cycle frequencies, the important contribution of movements in-and-out of the labor force argues for the introduction of a labor force participation decision margin in models of equilibrium unemployment. Moreover, the fact that quits and layoffs exhibit very different time series properties contrasts with the prediction of standard search and matching models (Mortensen and Pissarides, 1994) that quits and layoffs are indistinguishable. At low frequencies, the (labor supply driven) trend in unemployment correlates with a decline in the time-series volatility of business growth rates 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.

We conclude our paper by revisiting the behavior of the Beveridge curve over 1976-2009 through the lens of our unemployment decomposition. First, despite the many factors constantly shifting the U-V locus, the data do draw a downward slopping relationship between the unemployment rate and the job vacancy rate because shifts due to layoffs are highly correlated with movements along the curve. Second, the Beveridge curve progressively shifted to the left since 1976 because of the aging of the baby boom and because of women increasing attachment to the labor force. Third, the Beveridge curve exhibits counter-clockwise loops because, at the end of recessions, unemployment adjusts sluggishly to increases in vacancy posting and is temporarily off the Beveridge curve.

This 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

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

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 and Katz, 1986, 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, and Section 5 revisits our unemployment decomposition in the Beveridge curve space. Section 6 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.

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

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

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

$$u_t \simeq \frac{s_t}{s_t + f_t} \equiv u_t^{ss} \tag{2}$$

with s_t and f_t defined by

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

Expression (2) generalizes the simpler two-state case without movements in-and-out of the labor force where U_t satisfies $\dot{U}_t = \lambda_t^{EU} E_t - \lambda_t^{UE} U_t$ and $u_t^{ss} = \frac{\lambda_t^{EU}}{\lambda_t^{EU} + \lambda_t^{UE}}$. 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). As a result, f_t, the unemployment outflow rate that matters for steady-state unemployment rate is 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.

2.2 Modeling λ^{UE} with a matching function

The matching function relates the flow of new hires to the stocks of vacancies and unemployment. Like the production function, the matching function is a convenient device that partially captures a complex reality with workers looking for the right job and firms looking for the right worker. In a continuous time framework, the flow of hires can be modeled with a standard Cobb-Douglas matching function with constant returns to scale, and we can write

$$m_t = m_{0t} U_t^{\sigma} V_t^{1-\sigma} \tag{3}$$

with m_t, the number of new hires at instant t, U_t the number of unemployed, V_t the number of vacancies, and m_{0t} aggregate matching efficiency.[2]

Since the job finding rate λ_t^{UE} is the ratio of new hires to the stock of unemployed, we have $\lambda_t^{UE} = \frac{m_t}{U_t}$ so that $\lambda_t^{UE} = m_{0t}\theta_t^{1-\sigma}$with $\theta{=}\frac{v}{u}$ the aggregate labor market tightness, $u{=}U/LF$, $v{=}V/LF$ and LF the labor force. Specifically, we model λ_t^{UE} with

$$\ln \lambda_t^{UE} = (1-\sigma)\ln\theta_t + \ln m_0 + \varepsilon_t \tag{4}$$

with $\ln m_0$ the intercept of the regression. Aggregate matching efficiency is then given by

$$\ln m_{0t} = \ln m_0 + \varepsilon_t. \tag{5}$$

A number of factors can generate aggregate movements in matching efficiency: changes in workers' search intensity, changes in firms' recruiting intensity (Davis, Faberman and Haltiwanger, 2010), changes in the composition of the unemployment pool, or changes in the degree of misallocation (also called mismatch) between jobs and workers across labor market segments.[3]

[2]The Cobb-Douglas matching function is used in almost all macroeconomic models with search and search and matching frictions (e.g., Pissarides, 2001).

[3]In Barnichon and Figura (2010), we present an empirical framework to study the determinants of aggregate matching efficiency movements over 1976-2010.

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

$$u_t \simeq \frac{s_t}{s_t + \frac{\lambda_t^{UI}\lambda_t^{IE}}{1-\lambda_t^{II}} + \lambda_t^{UE}} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + m_{0t}\left(\frac{v_t}{u_t}\right)^{1-\sigma}} \tag{6}$$

with $\lambda_t^{UIE} = \frac{\lambda_t^{UI}\lambda_t^{IE}}{1-\lambda_t^{II}}$. Expression (6) is the theoretical underpinning of the Beveridge curve, the downward sloping relation between unemployment and vacancy posting. Unemployment moves along the Beveridge curve as firms adjust vacancies. Indeed, in a standard Mortensen-Pissarides (1994) model, the job creation condition $JC(\theta_t)$ determines the position of the unemployment rate on the Beveridge curve (6) as firms adjust vacancies in response to economic conditions (Figure 2). Changes in firms' labor demand translates into movements in θ_t, i.e. movements along the Beveridge curve (from point A to point B). But, as (6) shows, the Beveridge curve can also shift (from point B to point C) when s_t, λ_t^{UIE} or m_{0t} moves. Thus, the Beveridge curve can shift for very different reasons: changes in the intensity of layoffs and quits, changes in labor force participation, or changes in the efficiency of matching workers to jobs.

Log-linearizing (6) around the mean of the hazard rates gives us[4]

$$\begin{aligned} d\ln u_t^{ss} &= \alpha^{EI} d\ln\lambda_t^{EI} + \alpha^{IU} d\ln\lambda_t^{IU} + \alpha^{EU} d\ln\lambda_t^{EU} \\ &\quad -\alpha^{IE} d\ln\lambda_t^{IE} - \alpha^{UI} d\ln\lambda_t^{UI} - \alpha^{UE} d\ln m_{0t} - (1-\sigma) d\ln\theta_t + \eta_t \end{aligned} \tag{7}$$

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

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

[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 first- and second-order coefficients are shown in the Appendix.

where $d\ln u_t^{bc} \equiv -\alpha^{UE}(1-\sigma)d\ln\theta_t$ represents movements along the Beveridge curve, $d\ln u_t^{eff} \equiv -\alpha^{UE}d\ln m_{0t}$ captures the shifts in the Beveridge curve caused by changes 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

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

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

Different forces can shift the Beveridge curve. First, the Beveridge curve can shift if the employment-unemployment transition probability changes, and 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. Second, 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. Perry, 1970, Flaim, 1979, Shimer, 1998) 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.[5]

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.[6] 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 $(\frac{e_{it}^{ss}}{e_t^{ss}})$. In practice, the latter are small compared to the former, and $d\ln\lambda_t^{EU,demog}$ captures the movements in unemployment due to changes in the weight of each demographic group in the labor force.

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

[5] See the Appendix for more details.

[6] 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.

$\forall j \in \{p, t, q\}$.

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

$$\begin{cases} d\ln u_t^{bc} = -\alpha^{UE}(1-\sigma)d\ln\theta_t \\ d\ln u_t^{shifts,layoffs} = \alpha^{EU}\left(d\ln\tilde{\lambda}_t^{Ep} + d\ln\tilde{\lambda}_t^{Et}\right) \text{ and } d\ln u_t^{shifts,quits} = \alpha^{EU}d\ln\tilde{\lambda}_t^{Eq} \\ d\ln u_t^{shifts,LF-NLF} = \alpha^{EI}d\ln\tilde{\lambda}_t^{EI} + \alpha^{IU}d\ln\tilde{\lambda}_t^{IU} - \alpha^{IE}d\ln\tilde{\lambda}_t^{IE} - \alpha^{UI}d\ln\tilde{\lambda}_t^{UI} \\ d\ln u_t^{demog} = \alpha^{EI}d\ln\lambda_t^{EI,demog} + \alpha^{IU}d\ln\lambda_t^{IU,demog} + \alpha^{EU}d\ln\lambda_t^{EU,demog} \\ \qquad -\alpha^{IE}d\ln\lambda_t^{IE,demog} - \alpha^{UI}d\ln\lambda_t^{UI,demog} \\ d\ln u_t^{eff} = -\alpha^{UE}d\ln m_{0t} \end{cases}$$

We group the firm induced, or labor demand driven, movements in unemployment (due to vacancies or layoffs) under the heading "labor demand" and we group the worker induced, or labor supply driven, 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.

3 An empirical decomposition of unemployment fluctuations

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.[7] 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:[8]

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

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.

[7] 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).

[8] 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

$$\ln \lambda_t^{UE} = (1-\sigma)\ln \theta_t + \ln m_0 + \varepsilon_t \tag{16}$$

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 proxy for vacancy posting.[9] We use non-detrended data over 1967:Q1-2009:Q4, and 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). Using lagged values of v_t and u_t as instruments gives similar results, and the elasticity is little changed at 0.61. Figure 3 plots ε_t, the deviations of aggregate matching efficiency from its average level. While the matching function appears relatively stable over time, a corollary of the success of the matching function, aggregate matching efficiency displays a clear cyclical pattern. Matching efficiency typically lags the business cycle, increasing in the later stages of expansions or during recessions , peaking in the late stages of recessions or the early stages of recoveries, and declining thereafter. In the 2008-2009 recession however, the decline in matching efficiency occurred earlier than in previous recessions and was a lot more pronounced. In the fourth quarter of 2009, the residual reached an all time low.[10]

[9] 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.

[10] Elsby, Hobijn and Sahin (2010) report a similar finding using the unemployment outflow rate, and Davis, Faberman and Haltiwanger (2010) also report a dramatic decline in the vacancy yield using JOLTS data.

3.3 Labor demand driven and labor supply driven unemployment fluctuations

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 in matching efficiency.

To better visualize the contribution of each category in history, we temporarily depart from log-linearizing (2) around the mean of the hazard rates and instead log-linearize around the base date 2000q3.[11] That base date is attractive because it corresponds to the highest reading for vacancy posting per capita as well as the lowest value for $\ln u_t^{shift}$.[12] Figure 4 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 4 suggests that unemployment fluctuations are both labor demand- and labor supply-driven. However, the secular trend in unemployment appears to be labor supply driven, while the cyclical component of unemployment appears to be labor demand driven. 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, virtually all the trend in unemployment since 1976 is labor supply driven.[13] In contrast, 82 percent of unemployment's cyclical fluctuations is labor demand driven (excluding movements due to changes in matching efficiency). Nonetheless, the contribution of labor supply at cyclical frequencies is far from negligible at 19 percent.

With a contribution of 13 percent, changes in matching efficiency have, on average, a smaller

[11] 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.

[12] 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.

[13] To construct the decompositions of trend and cyclical unemployment, we decompose changes in unemployment into a trend component (from an HP-filter, $\lambda = 10^5$) and a cyclical component, and we separately apply decomposition (14) to each frequency range.

impact on the equilibrium unemployment rate, a corollary of the success of the matching function in modeling the job finding rate. However, Figure 4 shows low levels of matching efficiency in the aftermath of the 82 peaks in unemployment and during the 2008-2009 recession. Without any loss in matching efficiency, Figure 4 shows that unemployment would have been about 100 basis points lower in 1984 and about 150 basis points lower in end 2009.

3.4 The subcomponents of unemployment

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

Figure 5 and 6 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.

3.4.1 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, 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 procyclically.

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 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 5, 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 also strongly positively correlated with shifts due to layoffs and to movements along the Beveridge curve.

As we can see in Figure 6, movements in-and-out of the labor force contribute to some of the rise in unemployment during recessions. To visualize the role played by movements in-and-out of the labor force, Figures 7 to 10 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 7.[14] Comparing prime-age women with prime-age men in Figures 7 and 8, 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.[15] Further, older workers can also experience strong cyclical movements in λ^{IU} (Figure 9).[16]

[14] This could be due to the extension of unemployment benefits duration during recessions (see Barnichon and Figura (2010) for some evidence in this direction). 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.

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

[16] 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.

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 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.

3.4.2 Low-frequency movements:

A number of explanations have been advanced to explain the downward trend in unemployment since 1976 : the aging of the baby boom (Perry 1970, Flaim 1979, Shimer 1998, 2001), the decrease in men's labor force participation rate (Juhn, Murphy and Topel, 1991), and the increase in women's attachment to the labor force (Abraham and Shimer, 2001). However, absent an accounting framework to encompass all these hypotheses, there was no consensus on the quantitative role played by each explanation.

Using our framework, it is possible to quantify the contribution of each factor. Figure 6 confirms that the trend in unemployment originates in demographics ($d \ln u_t^{demog}$) and movements in and out of the labor force ($d \ln u_t^{shifts,LF-NLF}$), and Table 3 shows that these two factors can explain virtually all of the trend in unemployment, with movements in and out of the labor force accounting for about 60 percent of unemployment's trend and demographics about 40 percent.

To evaluate the direct role played by demographics, Figure 11 decomposes the movements in $d \ln u_t^{demog}$ plotted in Figure 6 into three components generated by the three demographic groups: Younger than 25, Prime-age female and Other. We can see that the aging of the baby boom is behind the contribution of demographics, as 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 much 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 females 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.

To explore the factors behind the trend in $d \ln u_t^{shifts,LF-NLF}$, we proceed in two steps. First, the upper-panel of Figure 12 decomposes the movements in $d \ln u_t^{shifts,LF-NLF}$ plotted in Figure 6 into four components generated by the four demographic groups: Prime-age male 25-55, Prime-age female 25-55, Younger than 25 and Over 55. We can see that the downward trend in $d \ln u_t^{shifts,LF-NLF}$ was caused by a change in the behavior of prime-age and young women. In contrast, a change in the behavior of men (such as the decrease in men's labor force participation rate identified by Juhn, Murphy and Topel, 1991) appears to have played a comparatively much smaller role. Second, it is easy to verify that the aggregate unemployment inflow rate $s_t = \lambda_t^{EU} + \frac{\lambda_t^{EI}\lambda_t^{IU}}{1-\lambda_t^{II}}$ displays a trend, but not the aggregate unemployment outflow rate $f_t = \lambda_t^{UE} + \frac{\lambda_t^{UI}\lambda_t^{IE}}{1-\lambda_t^{II}}$.[17] Thus, to understand the factors behind the trend in the unemployment rate coming from $d \ln u_t^{shifts,LF-NLF}$, one needs to study the behavior of λ_t^{EI} and λ_t^{IU} for women. Figure 7 shows that prime-age female displayed an increasing attachment to the labor force until the mid-90s as λ^{EI} was trending downwards, and women were increasingly unlikely to leave employment and drop out of the labor force.[18] After the mid-90s, λ^{EI} is roughly constant for women, but a secular decline in the rate at which women joined the

[17] f_t displays no trend because each hazard rate λ_t^{UE}, λ_t^{UI} and λ_t^{IE} displays no trend.

[18] While the other LF-NLF hazard rates also display a trend, decomposition (14) shows that, quantitatively, the effect of λ^{EI} dominates until the mid 90s. The downward trend in λ^{UI} also captures an increasing attachment to the labor force, but with the effect of raising, not lowering, the unemployment rate. The secular increase in λ^{IU} until the early 90s captures the fact that women were increasingly likely to join the labor force (the well-known increase in women's labor force participation rate), which raised the average unemployment rate since women have a higher unemployment rate than men.

labor force (trend in λ^{IU}) further lowered the unemployment rate. Similarly, a decline in the propensity of young workers to join the labor force (the downward trend in λ^{IU}) contributed to lower the aggregate unemployment rate.[19] To understand why men only had a small effect on unemployment's trend despite their lower labor force participation rate, Figure 8 plots the transition rates for prime-age males. Men display a decreasing attachment to the labor force as they have become more likely to leave to exit the labor market directly from employment (trend in λ^{EI}) and have become less likely to reenter the labor force once they leave it (trend in λ^{IU}).[20] While the trend in λ^{EI} raises the unemployment rate, the trend in λ^{IU} lowers it, so that the net effect of men's weaker labor force attachment is small.

Finally, our decomposition highlights a novel factor behind the downward trend in unemployment in the last 10-15 years: a decline in the rate of quits to unemployment ($d \ln u_t^{shifts,quits}$ in Figure 6). As shown in the lower-panel of Figure 12, the secular decline in quits can be traced back to a secular decline in the rate of quits to unemployment amongst men and women aged 16 to 35.[21]

Looking forward, two more recent labor supply trends are worth mentioning. First, Figure 9 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.[22] We can also notice an increase in labor force attachment as both λ^{UI} and λ^{EI} are following downward trends. Second, Figure 10 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. Extrapolating the trend in labor force participation

[19] Although Figure 12 shows $d \ln u_t^{shifts,LF-NLF}$ for male and female workers younger than 25, the trend is predominantly caused by female. The male-female distinction is left out in Figure 12 for clarity of exposition.

[20] This is consistent with Abraham and Shimer's (2001) finding that the labor-market-participation decisions of male and female have been converging.

[21] 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. See also Duca and Campbell (2007).

[22] This is especially true for women.

behavior since 2000 for young and old workers implies a steady-state unemployment rate about a quarter of a percentage point higher in 2015.[23]

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 (about 75 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, on average, small, but they 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, Haefke and Reiter 2006, and Campolmi and Gnocchi 2010) 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.[24]

Moreover, in the Mortensen-Pissarides model, quits and layoffs are indistinguishable since a match terminates when it is jointly optimal for both parties to separate. However, in the data,

[23] 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.

[24] 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).

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 understanding and modeling the factors behind matching efficiency movements (Figure 3) would be an important goal for future research.

Low-frequency movements: At low-frequencies, we found that, over 1976-2009, virtually all of the trend in the unemployment inflow rate s_t is labor supply driven and caused by secular changes in demographics and workers' attachment to the labor force. In contrast, the layoff rate displays no trend. Davis, Faberman, Haltiwanger, Jarmin and Miranda (2010) link the secular decline in the unemployment inflow rate to the secular decline in the job destruction rate. Since we can attribute the decline in s_t to demographics and behavioral changes in labor supply, our evidence suggests that the secular decline in job destruction is related to changes in labor supply rather than changes in labor demand.[25] Davis et al. (2010) also link the secular decline in the unemployment inflow rate to 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 the layoff rate 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 the layoff rate, as the micro evidence (Davis et al., 2010) suggests that a decrease in the variance of idiosyncratic shocks leads to a lower job destruction rate and a lower layoff rate.

[25] 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.

5 Looking back at the Beveridge curve

It is now instructive to restate some of our results in the Beveridge curve space and revisit the behavior of the Beveridge curve over 1976-2009 in light of our findings. We examine three key characteristics of the Beveridge curve: (i) Why does the Beveridge curve fit the data given the many factors constantly shifting the U-V locus?, (ii) Why did the Beveridge curve progressively shift to the left since 1976?, and (iii) Why does the Beveridge curve exhibit counter-clockwise loops?

5.1 The good fit of the Beveridge curve

Given the many factors constantly shifting the U-V locus at business cycle frequencies, it is surprising that the Beveridge curve fits the data so well and that one can observe movements along the curve. The reason, highlighted in Table 4, is that movements along the Beveridge curve are highly contemporaneously correlated with shifts due to layoffs, with a correlation of 0.88 for permanent layoffs. Thus, shifts from layoffs happen at the same time as movements along the curve. Because of such simultaneous shifts, the observed Beveridge curve is flatter than a curve generated solely by movements in vacancy posting. Figure 13 compares two counterfactual Beveridge curves; the first using a counterfactual unemployment rate generated only by movements in labor market tightness and the second using a counterfactual unemployment rate generated by movements along the curve and shifts due to layoffs. In both cases, the data draw a downward relationship between unemployment and vacancies, but the slope is flatter when we allow for shifts due to layoffs.

5.2 Why did the BC progressively shift to the left since 1976?

By isolating the component of unemployment driven by labor supply decisions, we can visualize the progressive leftward shift of the Beveridge curve caused by the effect of demographics and the stronger attachment of women to the labor force. Figure 14 and 15 plot two counterfactual Beveridge curves, one using a counterfactual unemployment rate generated only by shifts due to demographics, and the other generated only by shifts due to movements in and out of the labor force. The secular leftward shift is clearly apparent.

5.3 Why does the Beveridge curve exhibit counter-clockwise loops?

A well-known characteristic of the Beveridge curve is its tendency to draw counter-clockwise loops. Typically, at the end of recessions, vacancies improve in advance of unemployment. A common explanation for such counter-clockwise loops is that vacancies can be posted quickly, but that unemployment adjusts only sluggishly to the new equilibrium because of the frictions inherent in matching unemployed individuals to new jobs. As a result, unemployment is not always on its Beveridge curve. Since our framework is built on the assumption that unemployment adjusts very rapidly to its steady-state and is thus always on the Beveridge curve, we can use our framework to confirm the looping hypothesis.[26] Figure 16 plots a Beveridge curve implied by (6) and the steady-state assumption and shows that there is almost no more looping. Moreover, apart from looping, our Beveridge curve looks very similar to the empirical one (Figure 1), further confirming that the steady-state approximation is, on average, excellent and supporting our approach.

Our framework also suggests another reason for looping: the fact that workers respond to economic conditions (whether to quit or join/remain/leave the labor force) *with a lag* as they just their attachment to the labor force with a lag (Table 4).[27] Figure 15 plots a Beveridge curve generated only by shifts due to movements in and out of the labor force and shows that the lagged labor supply response does explain some of the looping in the 2008-2009 recession.

[26] This approximation is excellent in normal times, but it can deteriorate in recessions when the job finding rate is low. It is easy to show that in a 2-state model with employment and unemployment, unemployment converges to its steady-state value u_t^* according to $u_t = \nu_t u_t^* + (1-\nu_t)u_{t-1}$ with $\nu_{t+\tau} \simeq 1 - e^{-\lambda_t^{UE}}$. Given the magnitude of the job finding rate in the US, we have $u_t \simeq u_t^*$ at a quarterly frequency. A similar reasoning holds in a 3-state model with inactivity.

[27] Without a lag, as with shifts due to layoffs, the Beveridge curve would only be flatter and without loops.

6 Conclusion

This paper presents a framework to interpret movements in the Beveridge curve and decompose the components of unemployment fluctuations. We find that the cyclical fluctuations in unemployment are mostly labor demand driven but that movements in-and-out of the labor force play an important role and account for almost a quarter of unemployment's variance. Further, changes in labor demand lead changes in 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 is almost entirely labor supply driven, and caused in particular by the aging of the baby boom and the increasing attachment of women to the labor force. Finally, while changes in matching efficiency play, on average, a smaller role than movements in labor demand or labor supply, they can play a significant role during 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 investigate the forces behind the cyclical movements of 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

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

We solve that system numerically. Using the values for $\left\{U_{it}^{ss,j}\right\}_{j\in\{p,t,q,o\}}$, U_{it}^{ss}, E_{it}^{ss} and I_{it}^{ss}, the steady-state unemployment rate u_{it}^{ss} is then obtained from $u_{it}^{ss} = \frac{U_{it}^{ss}}{LF_{it}^{ss}}$, i.e.,

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

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

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

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 $d\varepsilon_t = \frac{d\lambda_t^{UE}}{\lambda^{UE}} - \frac{d\hat{\lambda}_t^{UE}}{\lambda^{UE}} - \left(\frac{d\lambda_t^{UE2}}{\lambda^{UE2}} - \frac{d\hat{\lambda}_t^{UE2}}{\lambda^{UE2}}\right)$, so that by defining $d\varepsilon_t^1 = \frac{d\lambda_t^{UE}}{\lambda^{UE}} - \frac{d\hat{\lambda}_t^{UE}}{\lambda^{UE}}$ and $d\varepsilon_t^2 = \frac{d\lambda_t^{UE2}}{\lambda^{UE2}} - \frac{d\hat{\lambda}_t^{UE2}}{\lambda^{UE2}}$, 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)[28] that we multiply by the average growth rate of the transition probability over 1994m1-2009. That

[28] Taking 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. Indeed, 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.

References

[1] Abraham, K. "Help-Wanted Advertising, Job Vacancies, and Unemployment," *Brookings Paper on Economic Activity*, 1:207-248, 1987.

[2] Abraham, K and L. Katz. "Cyclical unemployment: Sectoral Shifts or Aggregate Disturbances," *Journal of Political Economy*, 507-22, 1986.

[3] Abraham, K. and R. Shimer. "Changes in Unemployment Duration and Labor-Force Attachment." In The Roaring Nineties: Can Full Employment Be Sustained?, ed. Alan B. Krueger and Robert M. Solow, 367-420. New York: Russell Sage Foundation and Century Foundation Press, 2001.

[4] Barnichon, R. "Building a composite Help-Wanted index," *Economics Letters*, Forthcoming, 2010.

[5] Barnichon, R. and A. Figura. "What drives matching efficiency? A tale of composition and dispersion," mimeo, 2010.

[6] Blanchard O. and P. Diamond. "The Beveridge Curve," *Brookings Paper on Economic Activity*, 1:1-60, 1989.

[7] Campolmi, A. and S. Gnocchi. "Labor Market Participation, Unemployment and Monetary Policy," Working Paper, 2010.

[8] Davis, S., J. Faberman, and J. Haltiwanger. "The Flow Approach to Labor Markets: New Evidence and Micro-Macro Links." *Journal of Economic Perspectives*, 20(3), 3-26, 2006.

[9] Davis, S., J. Faberman and J. Haltiwanger. "The Establishment-Level Behavior of Vacancies and Hiring," NBER Working Paper, 2010.

[10] Davis, S., J. Faberman, J. Haltiwanger, R. Jarmin, J. Miranda. "Business Volatility, Job Destruction and Unemployment." *American Economic Journal: Macroeconomics*, 2010.

[11] Duca J. and C. Campbell."The impact of evolving labor practices and demographics on U.S. inflation and unemployment," Dallas Fed Working Paper, 2007.

[12] Elsby, M. B. Hobijn and A. Sahin. "Unemployment Dynamics in the OECD," Working Paper, 2008.

[13] Elsby, M. R. Michaels and G. Solon. "The Ins and Outs of Cyclical Unemployment," *American Economic Journal: Macroeconomics,* 2009.

[14] Fallick, B. and C. Fleischman. "Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," Finance and Economics Discussion Series 2004-34, 2004.

[15] Flaim, P. "The Effect of Demographic Changes on the Nation's Unemployment Rate," *Monthly Labor Review*, 3-10, 1979.

[16] Fujita, S. and G. Ramey. "The Cyclicality of Separation and Job Finding Rates," *International Economic Review*, 2009.

[17] Juhn, C., K. Murphy and R. Topel. "Why has the Natural Rate Increased over Time," *Brookings Papers on Economic Activity,* (2) pp75-142, 1991.

[18] Lipsey, R. "Structural and Deficient-Demand Unemployment Reconsidered," in *Employment Policy and the Labor Market*, ed. Arther M. Ross, 210-255, UC Berkeley Press, 1965.

[19] Mortensen, D and C. Pissarides. "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61, 397-415, 1994.

[20] Perry, G. "Changing Labor Markets and Inflation," *Brookings Papers on Economic Activity*, 411-441, 1970.

[21] Petrongolo, B. and C. Pissarides. "Looking into the black box: A survey of the matching function," *Journal of Economic Literature*, 39: 390-431, 2001.

[22] Pissarides, C. *Equilibrium Unemployment Theory*, 2nd Edition, MIT Press, 2001

[23] Polivka, A. and S. Miller. "The CPS After the Redesign: Refocusing the Economic Lens." in Labor Statistics and Measurement Issues, edited by John Haltiwanger, Marilyn Manser, and Robert Topel. University of Chicago Press, 1998.

[24] Rogerson, R. and R. Shimer " Search in macroeconomic models of the labor market," *Handbook of Labor Economics*, Forthcoming, 2010.

[25] Sahin, A., J. Song, and B. Hobijn, "The Unemployment Gender Gap During the Current Recession, " mimeo, FRB-NY, 2009.

[26] Shimer, R., "Why is the U.S. Unemployment Rate So Much Lower?" *NBER Macroeconomics Annual*, ed. by Ben Bernanke and Julio Rotemberg, vol. 13. MIT Press, Cambridge, MA, pp. 11-61, 1998.

[27] Shimer, R., "The Impact of Young Workers on the Aggregate Labor Market," Quarterly Journal of Economics, 116, 969-1008, 2001.

[28] Shimer, R. "Reassessing the Ins and Outs of Unemployment," NBER Working Paper No. 13421, 2007.

[29] Zagorsky, J., "Job Vacancies in the United States: 1923 to 1994", *Review of Economics and Statistics*, vol.80, no. 2, May 1998, pp. 338-45.

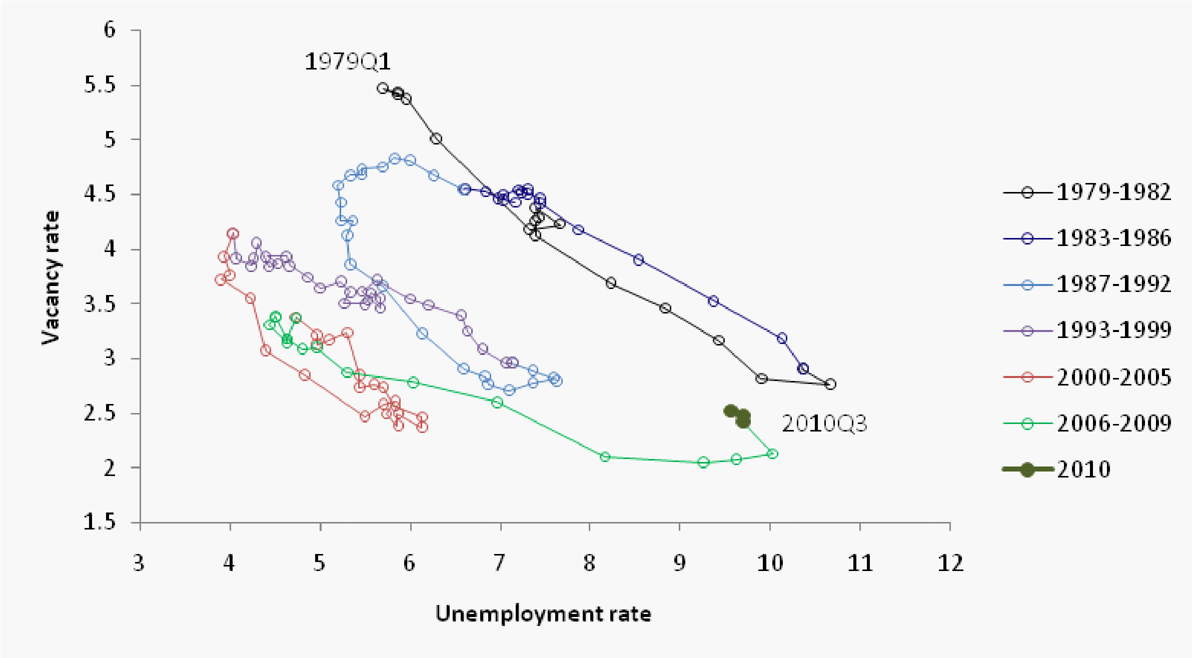

Figure 1: The US Beveridge curve, 1979Q1-2010Q3.

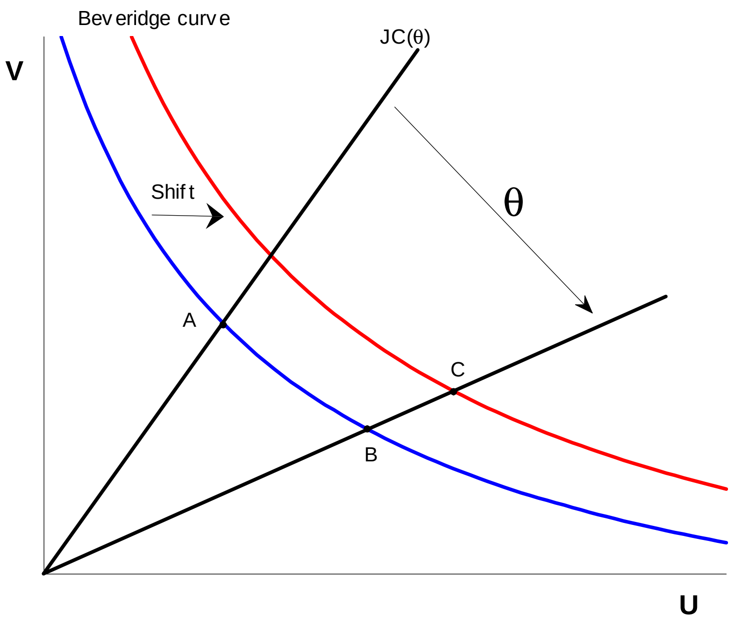

Figure 2: The Beveridge curve: shifts and movement along the curve.

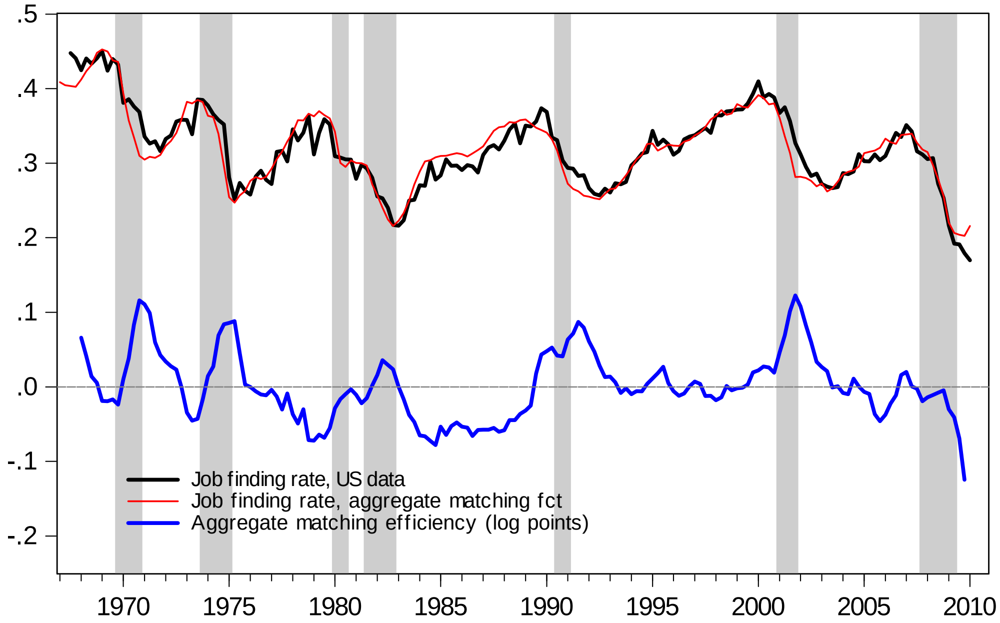

Figure 3: Empirical job finding rate, job finding rate predicted by an aggregate matching function and (log) aggregate matching efficiency, the (log) difference between the empirical and the predicted job finding rate, 1967-2009. For aggregate matching efficiency, the plotted series is the 4-quarter moving average. Grey bars indicate NBER recession dates.

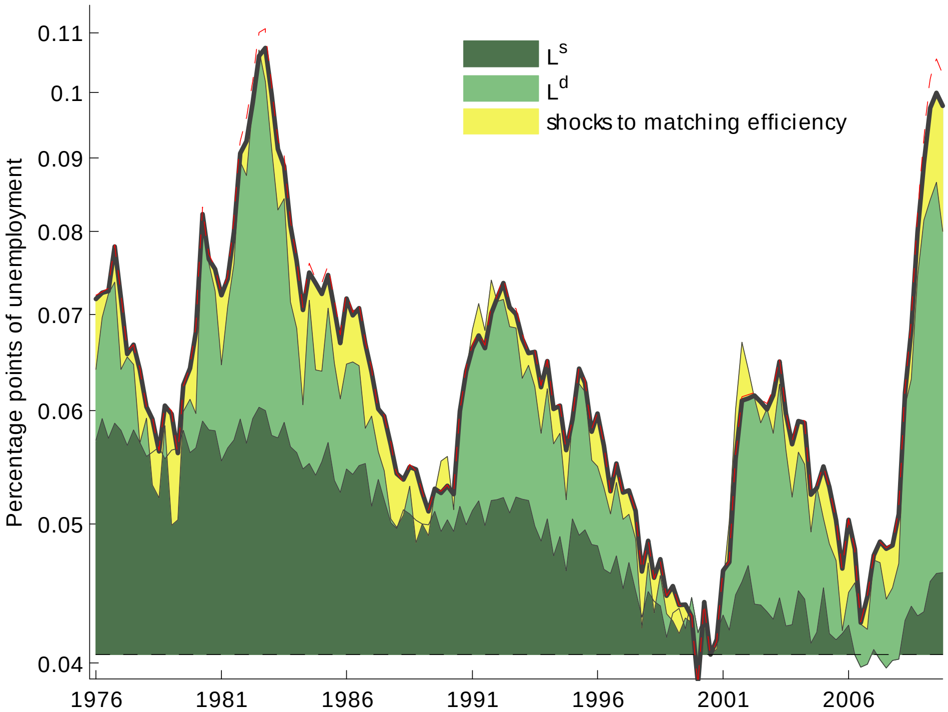

Figure 4: Decomposition of unemployment fluctuations into labor demand movements, labor supply movements and shocks to matching efficiency over 1976-2009. The y-axis uses a logarithmic scale. The decomposition uses 2000Q3 as the base year. The colored areas sum to the approximated steady-state unemployment. The dashed red line is the exact value of steady-state unemployment.

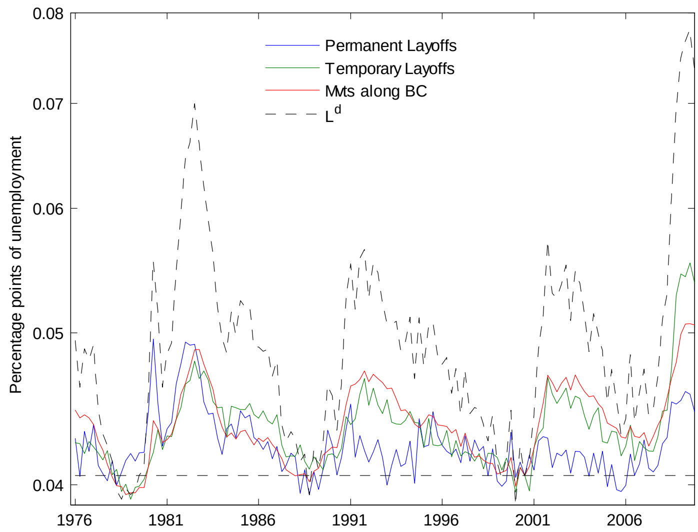

Figure 5: Decomposition of labor demand movements into movements along the Beveridge curve and Beveridge curve shifts from permanent layoffs or temporary layoffs, 1976-2009. The decomposition uses 2000Q3 as the base year. The y-axis uses a logarithmic scale.

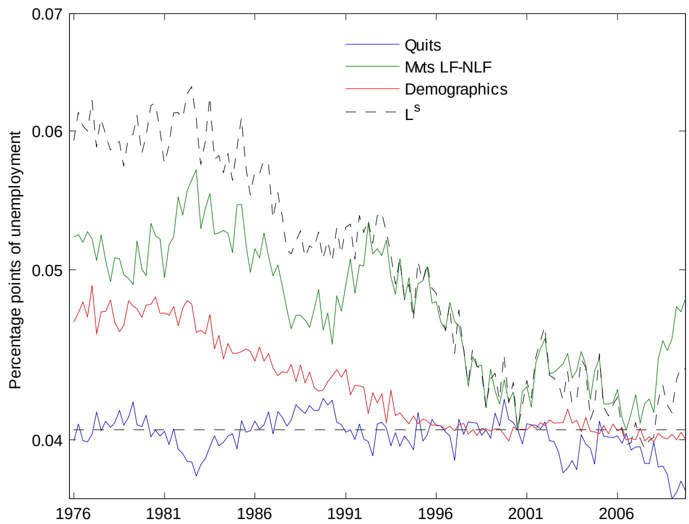

Figure 6: Decomposition of labor supply movements into Beveridge curve shifts due to quits, movements in-and-out of the labor force and demographics, 1976-2009. The decomposition uses 2000Q3 as the base year. The y-axis uses a logarithmic scale.

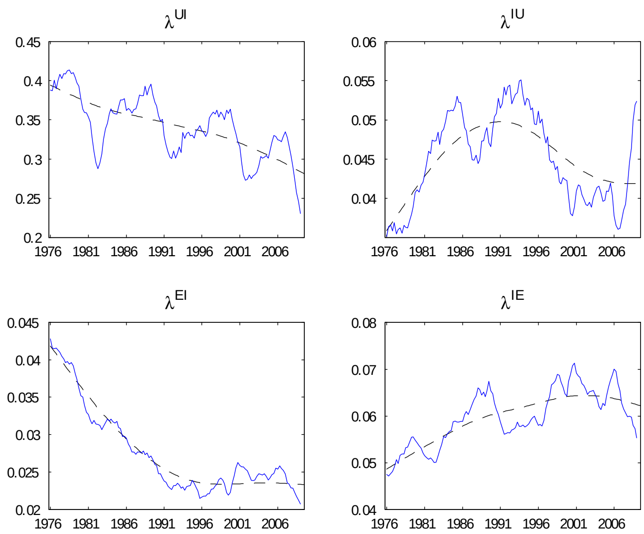

Figure 7: Transition rates for in-and-out of the labor force movements for women aged 25-55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

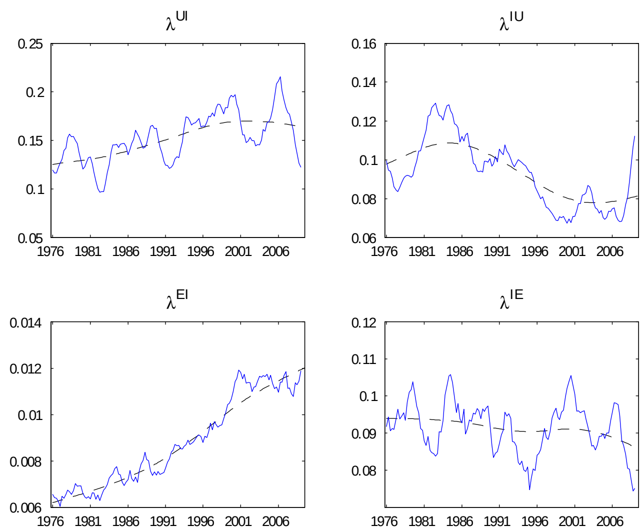

Figure 8: Transition rates for in-and-out of the labor force movements for men aged 25-55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

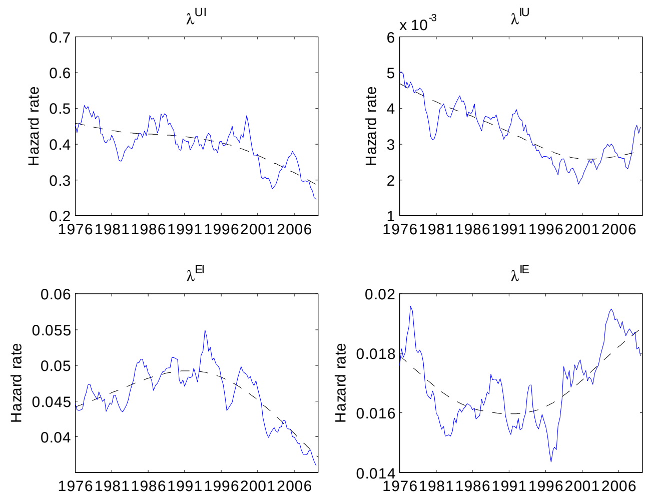

Figure 9: Transition rates for in-and-out of the labor force movements for men and women aged over 55, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

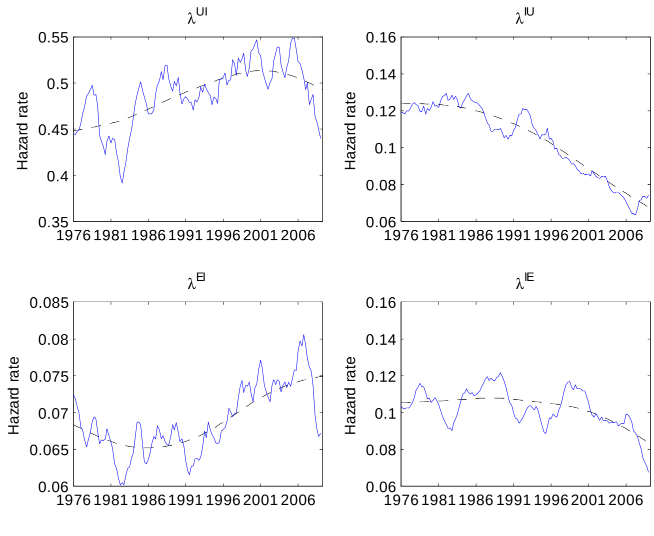

Figure 10: Transition rates for in-and-out of the labor force movements for men and women aged 16-25, 1976-2009. The dashed line represents the corresponding HP-filter trend ($\lambda = 10^5$).

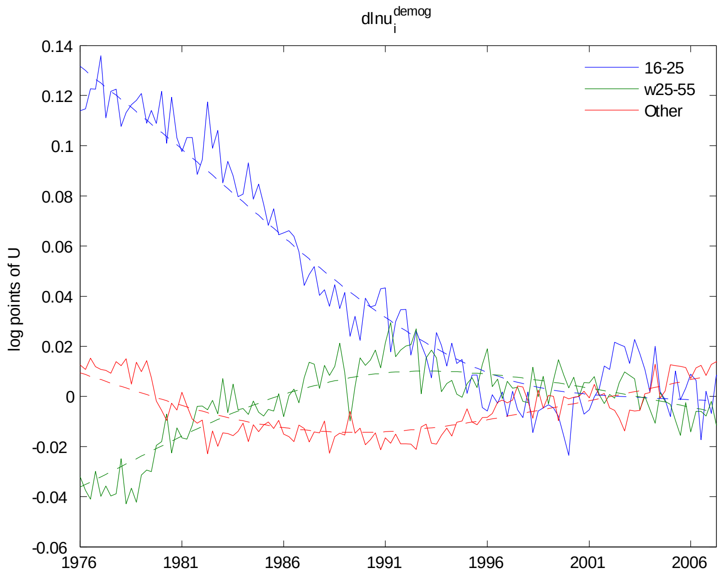

Figure 11: Contribution of three demographic groups (16-25, female 25-55 and Other) to the Beveridge curve shifts due to changes in the demographics of the labor force ($d\ln u_{it}^{shifts,LF-NLF}$). The dashed lines represent the corresponding HP-filter trend (λ=10^5), 1976-2009.

Figure 12: Decomposition of Beveridge curve shifts by demographics. Upper panel: Beveridge curve shifts due to movements in and out of the labor force ($d \ln u_{it}^{shifts,LF-NLF}$) for four demographic groups, Male 25-55, Female 25-55, 16-25 and Over 55. Lower panel: Beveridge curve shifts due to quits ($d \ln u_{it}^{shifts,quits}$) for two demographic groups: 16-35 and Older than 35. The dashed lines represent the corresponding HP-filter trends (λ=10^5), 1976-2009.

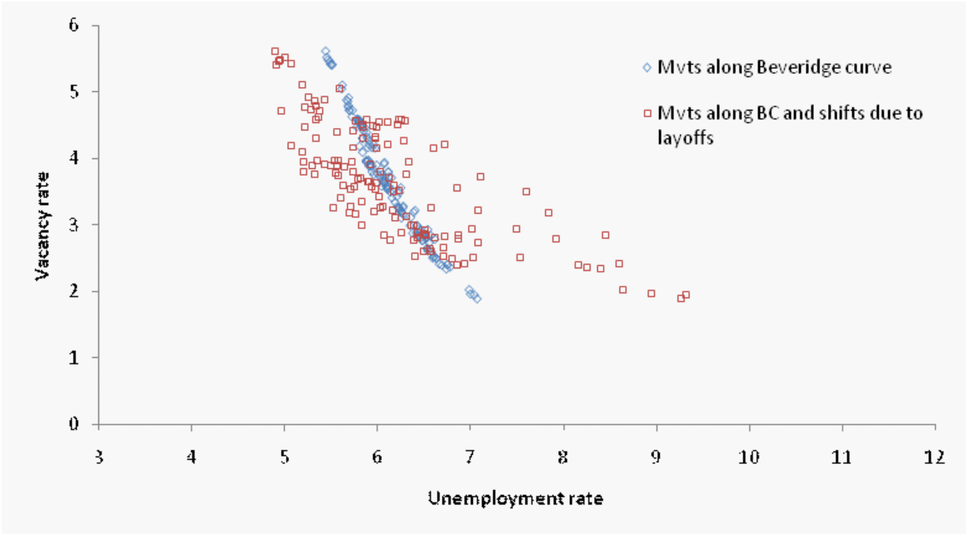

Figure 13: Counterfactual Beveridge curves, 1976-2009. Blue circles: counterfactual Beveridge curve using the unemployment rate implied by movements in labor market tightness. Red squares: counterfactual Beveridge curve using the unemployment rate implied by movements in labor market tightness and shifts due to layoffs.

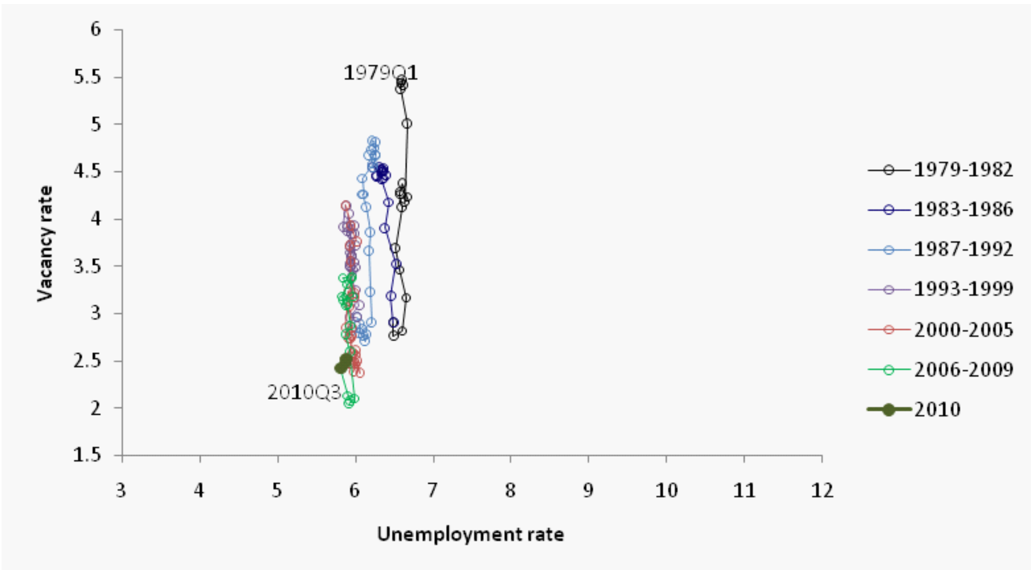

Figure 14: Counterfactual Beveridge curve using the unemployment rate generated by changes in demographics.

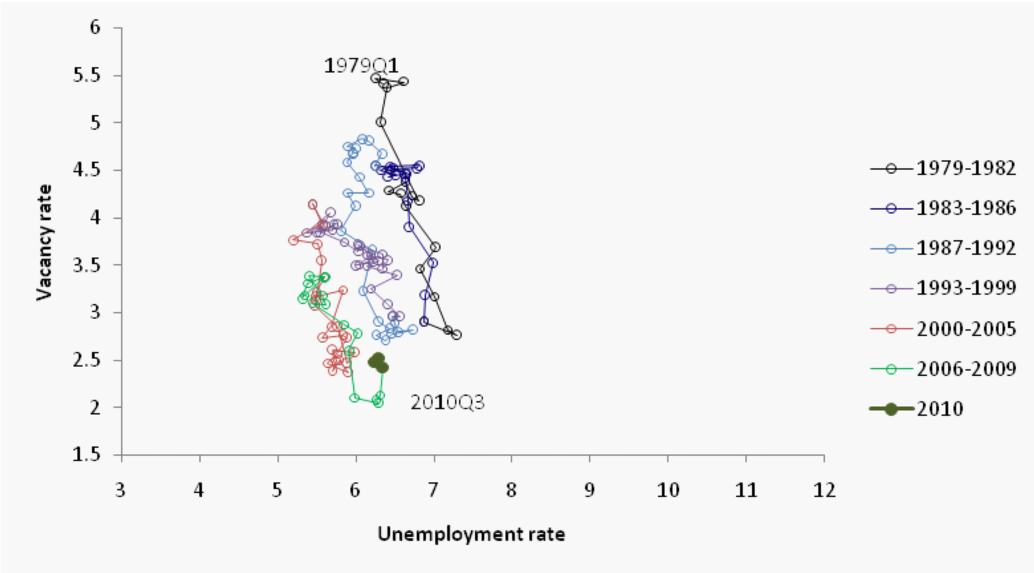

Figure 15: Counterfactual Beveridge curve using the unemployment rate generated by movements in and out of the labor force.

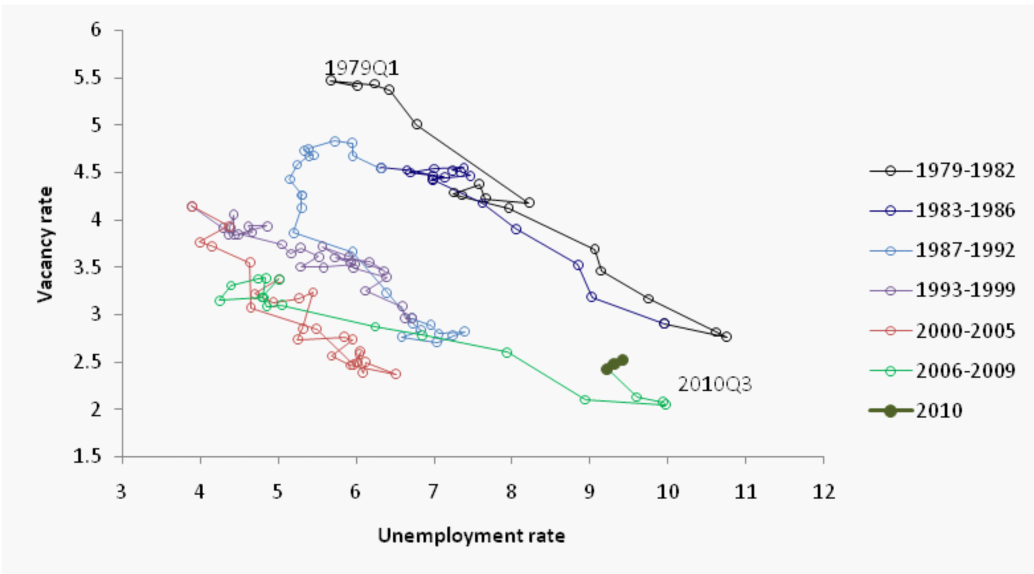

Figure 16: Counterfactual Beveridge curve using the unemployment rate generated by movements in labor demand, labor supply, and changes in matching efficiency.

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***	0.61***
	(0.01)	(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).