The Determinants of the Cycles and Trends in U.S. Unemployment since 1976*

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Abstract

In this paper, we decompose U.S. unemployment movements into the contributions of four economic forces –hiring, layoff, quit, labor market participation decisions– and changes in demographics. At business cycle frequencies, hiring and layoffs are the main determinants of unemployment fluctuations, consistent with standard business cycle models of the labor market (Mortensen-Pissarides, 1994). At low frequencies, the downward trend in unemployment since the mid-70s can be attributed to the aging of the baby boom and to a downward trend in labor supply, but not to trends in hiring and layoffs. Our results imply that the gradual leftward shift of the Beveridge curve over the last 40 years owes to demographic factors and lower labor supply, but not to improvements in the efficiency of the matching process or to changes in firms' hiring and layoff policies.

JEL classifications: J6, E24, E32

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1 Introduction

The unemployment rate is an important indicator of economic activity. Understanding the nature of unemployment 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 US unemployment rate has displayed large fluctuations over the post war period, both at cyclical and low-frequencies, but, despite decades of research, the determinants of unemployment movements are still imperfectly understood. In particular, while it is generally assumed that cyclical fluctuations in unemployment owe to movements in labor demand (e.g., Mortensen-Pissarides, 1994), there is no clear consensus on the role played by the labor force participation margin. At low frequencies, while unemployment has displayed a downward trend over the last 35 years, there is yet no consensus on the extent to which the trend owes to labor supply factors (such as lower labor force participation or changes in demographics) and to labor demand factors (such as increasing wage flexibility).[1] Finally, while it is common practice to treat separately cyclical and low frequencies, the cycle-trend dichotomy is not necessarily justified since the factors determining long-run unemployment movements need not be distinct from those determining cyclical fluctuations.[2]

To study the economic forces behind unemployment fluctuations, this paper presents an accounting framework that decomposes unemployment fluctuations into the contributions of hiring, layoffs, quits, labor market participation decisions, and demographics. Importantly, our framework covers all frequency and does not a priori treat separately business cycle frequencies and low-frequencies.

We find that most of the trend in unemployment can be attributed to labor supply factors –the aging of the baby boom and a decline in labor supply–, but not to labor demand factors and trends in hiring and layoffs. In contrast, at business cycle frequencies, hiring and layoffs are the prime determinants of unemployment fluctuations. Our results thus justify, although only *ex-post* and for the U.S. only, the trend-cycle dichotomy.

Our starting point is a simple stock-flow model of unemployment in steady-state, as in Shimer (2007). Workers can transit between three labor market states: employment (E), unemployment (U) and inactivity (I) (i.e., out of the labor force). The steady-state unem-

[1] Hypotheses include the aging of the baby boom (Perry 1970, Flaim 1979, Bleakley and Fuhrer 1997, 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). In addition, labor demand based explanations have also been suggested, such as increasing wage flexibility (Davis, Faberman and Haltiwanger, 2006) or declining intensity of idiosyncratic labor demand shocks (Davis, Faberman, Haltiwanger, Jarmin and Miranda, 2010).

[2] For instance, the factors behind the trend in unemployment could also affect the business cycle properties of unemployment fluctuations.

ployment rate is then characterized by six transition rates (corresponding to the six possible transitions). Since changes in demographics are known to mechanically affect unemployment movements at all frequencies, we first control for changes in demographics and construct demographic-adjusted transition rates using CPS matched micro data over 1976-2010.[3] We then interpret these six hazard rates in terms of four economic mechanisms: hiring, layoff, quit, and labor market participation decisions. To do so, we proceed as follows. First, we model the unemployment-employment (UE) flows with an aggregate matching function tying new matches to job openings and unemployment, so that we can interpret the component of UE driven by changes in labor market tightness (the vacancy-unemployment ratio) in terms of firms' hiring policies. Second, to interpret employment-unemployment transitions, we separate transitions according to the source of the separation: a layoff, initiated by the firm, or a quit, initiated by the worker. Third, we interpret the employment-inactivity and unemployment-inactivity transition rates as capturing the propensity of individuals to exit the labor force. The last term appearing in our unemployment decomposition is the probability that inactive individuals find a job conditional on joining the labor force. We argue that this term depends on two factors: (i) firms' hiring efforts and (ii) the fraction of marginally attached individuals, which, we argue, captures the extent to which inactives are interested in the labor market and in getting jobs, and thus captures changes in the economy's labor supply.[4]

At business cycle frequencies, hiring and layoffs account for most of unemployment's variance, a result in line with the approach taken by the search and matching literature and the canonical Mortensen-Pissarides (1994) model to focus on job creation and job separation when studying unemployment fluctuations. Nonetheless, labor market participation decisions, in particular labor force exits and the attachment of inactives to the labor force, exacerbate unemployment fluctuations. In recessions, unemployed workers are more likely to remain in the labor force, and inactive individuals have a stronger attachment to the labor force and are more likely to join the unemployment pool, which raises unemployment. Our findings thus call for a better understanding of the forces driving individuals decisions to want a job, look for a job or stay inactive and lends support to recent theoretical effort aimed at understanding the determinants of labor force participation.[5] Finally, while changes in matching efficiency

[3] Fujita and Ramey (2006) and Elsby, Hobijn and Sahin (2010) showed that the transition rates can differ markedly across demographic groups, not only in level but also in cyclical volatility. Moreover, a number of studies have argued that the aging of the baby boom played an important role in explaining the trend in unemployment (e.g., Perry 1970, Flaim 1979, Shimer 1998, 2001).

[4] Marginally attached individuals are defined as individuals who want a job but are not looking for one, and are thus out of the labor force.

[5] See Garibaldi and Wasmer (2005), Haefke and Reiter (2006), Campolmi and Gnocchi (2010), Gali (2010), Krussel, Mukoyama, Rogerson and Sahin (2011a, 2011b) for recent efforts to introduce a labor force participation decision.

play, on average, a smaller role, 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.

Turning to low frequencies, while a number of hypotheses have been advanced to explain the trend in unemployment since 1976, no clear consensus has emerged regarding the relative importance of these hypotheses. Our accounting framework allows us to discriminate amongst competing explanations, and we propose a new explanation related to the composition of the inactivity pool. We find that the trend in unemployment is driven by (i) demographics (for about 40 percent), specifically the aging of the baby boom generation, (ii) increasing attachment of women to labor force until the early 90s, and (iii) after the early 90s, a downward trend in the fraction of marginally attached individuals. Marginally attached have a higher propensity to find a job than inactive individuals but an even higher propensity to join the unemployment pool. As a result, a higher fraction of marginally attached individuals raises the unemployment rate. The 1990s saw a downward trend in the fraction of marginally attached workers that lead to a 3/4ppt decline in the unemployment rate. In turn, we show that this downward trend was caused by an increase in the propensity of marginally attached workers to give up wanting a job, and a decline in the propensity of inactive individuals to want to job. We conclude that a significant fraction of the downward trend in unemployment since the mid-90s is due to a shrinking of the economy's labor supply, defined by including any individual who wants or has a job. To dig deeper into the mechanisms behind such trends, we analyze the behavior of behavior of demographic sub-groups. Up until the mid-90s, unemployment's trend owes to a downward trend in women propensity to exit the labor force, but since the mid-90s, it owes to a downward trend in labor force entry amongst all demographic groups.[6] The downward trend in inactives attachment to the labor force can be observed for all demographic groups except older individuals and is most pronounced for young individuals.

Since we find no evidence of a trend in the component of unemployment driven by firms' hiring and layoff policies, our results suggest that labor demand explanations of unemployment's trend, such as increasing wage flexibility or declining intensity of idiosyncratic labor demand shocks, played a less direct role than typically assumed, because they did not trigger a downward trend in the layoff rate to unemployment –the hazard rate of being laid-off and becoming unemployed–. Davis et al. (2010) link the downward trend in the unemployment inflow rate to a secular decline in business variability and a decline in the job destruction rate. Our decomposition suggests that explanations of such declines may lie with demographics and secular changes in workers' behavior, given the absence of a trend in the layoff rate to unem-

[6] However, given their higher unemployment rate, young workers' contribution explains almost half of the contribution of labor force entry.

ployment. This result is in line with the recent findings of Jaimovich and Siu (2009) who find that changes in the age composition of the labor force account for a significant fraction of the variation in postwar business cycle volatility. In a similar vein, an explanation of the puzzling low-frequency correlation between productivity growth and unemployment (Staiger, Stock and Watson, 2001) may lie with demographics and workers' behavior.

We conclude our paper by revisiting the behavior of the empirical Beveridge curve, the downward sloping relation between unemployment and vacancy posting, over the last 40 years through the lens of our unemployment decomposition. Since the influential works of Abraham and Katz (1986) and Blanchard and Diamond (1989), the Beveridge curve is widely used as an indicator of the state of the labor market.[7] Movements along the Beveridge curve, i.e., changes in unemployment due to changes in vacancies, are typically interpreted as cyclical movements in labor demand. Shifts in the Beveridge curve, however, 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 various factors, from cyclical factors, such as changes in the intensity of layoffs, to structural factors, such as demographic changes. Our results imply that the gradual leftward shift in the U-V locus since 1976 owes to the aging of the baby boom generation and to a decline in the economy's labor supply, but not to improvements in the efficiency of the matching process or to changes in firms' hiring and layoff policies.

Our paper builds on an important literature, going back at least to Darby, Haltiwanger and Plant (1986), that aims to understand the determinants of unemployment fluctuations by studying the flows of workers in and out of unemployment.[8] Typically, such decompositions between the "Ins" and "Outs" have aimed to determine whether increased unemployment during recessions arise from an increase in the number of unemployment spells or an increase in the duration of these spells. Our paper extends that literature in three directions. First, while the worker flows literature focused solely on business cycle frequencies, our decomposition covers all frequencies. Second, while the literature typically focuses on aggregate worker flows,[9] our decomposition emphasizes the importance of heterogeneity across demographics groups, both at low and business cycle frequencies. Finally, rather than focusing on the flows, our decomposition focuses on the economic decisions behind unemployment movements. The two approaches are closely related, but our different perspective can provide a number of additional insights, because decompositions between the "Ins" and "Outs" are sometimes hard

[7] See also Bleakley and Fuhrer (1997).

[8] See, among others, Blanchard and Diamond (1989, 1990), Bleakley, Ferris and Fuhrer (1999), Shimer (2007), Petrongolo and Pissarides (2008), Elsby, Michaels and Solon (2009), Fujita and Ramey (2009), Elsby, Hobijn, and Sahin (2010, 2011).

[9] An exception is Elsby, Hobijn and Sahin (2010) who study the business cycle movements of the inflows and outflows of unemployment in a two labor market states context.

to interpret. Indeed, different economic forces can generate changes in the number of exits or in the number of entries. For instance, finding a job and leaving the labor force are both unemployment outflows. A layoff, a quit and an entry to the labor force are all unemployment inflows. Moreover, observing increased flows from out of the labor force to employment does not tell us whether those increased flows occurred because of a higher job finding probability of the inactive (related to more hiring) or because more inactive individuals decided they wanted a job and joined the labor force. By addressing these shortcomings, our approach can provide additional information on the determinants of unemployment movements and useful inputs into the development of models. Another advantage is that our decomposition maps directly with policy options. By identifying the respective roles of job creation, layoff and labor market participation in driving unemployment higher in recessions, our decomposition can inform the policy debate on the desirability of different options, and in particular, the desirability of a job creation subsidy versus a firing tax versus an employment tax credit (that rewards labor market entry).

The next section lays the theoretical groundwork for our decomposition. Section 3 presents our interpretation of the six hazard rates. Section 4 presents our results and Section 5 discusses their implications of our results, and Section 6 revisits our unemployment decomposition in Beveridge curve space. Section 7 concludes.

2 An unemployment accounting framework

In this section, we present an accounting framework that isolates the main economic forces driving unemployment: hiring, layoff, quit, labor force entry, labor force attachment and changes in the demographic structure of the labor force.

2.1 Accounting for demographics

The aggregate unemployment rate reflects the labor market experience of demographics groups with different and time varying characteristics. A number of researchers (e.g., Perry, 1970, Flaim, 1979, Shimer, 1998) have emphasizes that demographic change has 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 aggregate unemployment rate goes down. Moreover, an abundant literature has documented differences in the cyclical sensitivity of different demographic groups (see Clark and Summers 1981). For instance, young workers have a higher turnover than older workers but also a less volatile unemployment rate (e.g., Fujita and Ramey 2006, Elsby, Hobijn an Sahin, 2010). Thus, changes in demographics could also have an impact on the cyclicality of aggregate unemployment.

Thus, before interpreting labor market flows, we allow for heterogeneity across demographic groups. Formally, denote $u_{it} = \frac{U_{it}}{LF_{it}}$ the unemployment rate of demographic groups $i \in \{1, .., N\}$, with U_{it} the number of unemployed of type i and LF_{it} the size of the labor force of the corresponding labor force. Denote $\omega_{it} = \frac{LF_{it}}{LF_t}$ the share of group i in the labor force.

The aggregate unemployment rate is given by

$$u_t = \sum_{i=1}^{N} \omega_{it} u_{it}$$

so that movements in unemployment can be decomposed from

$$du_t = \sum_{i=1}^{N} \left(\omega_i \frac{u_i}{u} d\omega_{it} + \omega_i \frac{u_i}{u} du_{it} \right). \tag{1}$$

2.2 Steady-state unemployment

In demographic group i, let U_{it}, E_{it}, and I_{it} denote the number of unemployed, employed and inactive (out of the labor force), respectively, at instant $t \in \mathbb{R}_+$. Letting λ_{it}^{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

$$\begin{cases} \dot{U}_{it} = \lambda_{it}^{EU} E_{it} + \lambda_{it}^{IU} I_{it} - (\lambda_{it}^{UE} + \lambda_{it}^{UI}) U_{it} \\ \dot{E}_{it} = \lambda_{it}^{UE} U_{it} + \lambda_{it}^{IE} I_{it} - (\lambda_{it}^{EU} + \lambda_{it}^{EI}) E_{it} \\ \dot{I}_{it} = \lambda_{it}^{EI} E_{it} + \lambda_{it}^{UI} U_{it} - (\lambda_{it}^{IE} + \lambda_{it}^{IU}) I_{it} \end{cases} \tag{2}$$

In the U.S., the magnitudes of the hazard rates are such that the half-life of a deviation of unemployment from its steady state value is about one to two month. As a result, at a quarterly frequency, the unemployment rate $u_{it} = \frac{U_{it}}{LF_{it}}$ is very well approximated by its steady-state value u_{it}^{ss} so that[10]

$$u_{it} \simeq \frac{s_{it}}{s_{it} + f_{it}} \equiv u_{it}^{ss} \tag{3}$$

with s_{it} and f_{it} can be written

$$\begin{cases} f_{it} = \lambda_{it}^{UE} + \lambda_{it}^{UI} \lambda_{it}^{IE|ILF} \\ s_{it} = \lambda_{it}^{EU} + \lambda_{it}^{EI} \left(1 - \lambda_{it}^{IE|ILF} \right) \end{cases} \tag{4}$$

where $\lambda_{it}^{IE|ILF} = \frac{\lambda_{it}^{IE}}{\lambda_{it}^{ILF}}$ and $\lambda_{it}^{ILF} = \lambda_{it}^{IE} + \lambda_{it}^{IU}$.

[10]Shimer (2007) made this point using aggregate hazard rates.

Expression (3) generalizes the simpler two-state case without movements in-and-out of the labor force where U_{it} satisfies $\dot{U}_{it} = \lambda_{it}^{EU} E_{it} - \lambda_{it}^{UE} U_{it}$ and $u_{it}^{ss} = \frac{\lambda_{it}^{EU}}{\lambda_{it}^{EU}+\lambda_{it}^{UE}}$. 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-E). As a result, f_{it}, the unemployment outflow rate that matters for steady-state unemployment rate is a weighted average of λ_{it}^{UE} and $\lambda_{it}^{UI} \lambda_{it}^{IE}$, with weights of 1 and $\frac{1}{\lambda_{it}^{IU}+\lambda_{it}^{IE}}$, the average time that a worker going U->I->E spends transitioning through state I. s_{it} has a similar expression since $1 - \lambda_{it}^{IE|ILF} = \lambda_{it}^{IU} / \lambda_{it}^{ILF}$.

2.3 Aggregating across demographic groups

By taking a Taylor expansion of (3) and (4) around the mean of the hazard rates for each demographic group i, we can decompose the unemployment rate u_{it} as a linear function of changes in the hazard rates[11]

$$du_{it} = \sum_{A \neq B} \alpha_i^{AB} d\lambda_{it}^{AB} + \eta_{it} \text{ with } A, B \in \{U, E, I\}, \quad \alpha_i^{AB} \in \mathbb{R}$$

so that the aggregate unemployment rate can be decomposed as

$$du_t = \sum_{i=1}^{N} \omega_i \frac{u_i}{u} d\omega_{it} + \sum_{A \neq B} \sum_{i=1}^{N} \omega_i \frac{u_i}{u} \alpha_i^{AB} d\lambda_{it}^{AB} + \eta_t. \tag{5}$$

Starting from (5), our goal is to decompose movements in unemployment into meaningful economic concepts. However, the hazard rates λ_{it}^{AB} need not correspond immediately to economic concepts such as hiring, layoff or labor force entry. In the next section, we thus describe a method to interpret the different components λ_{it}^{AB}.

3 An economic interpretation of unemployment fluctuations

3.1 Interpreting movements in the job finding rate

To interpret movements in unemployment due to changes in job finding probability, we use a matching function, a device commonly found in macroeconomic models with search and search and matching frictions (e.g., Pissarides, 2001). We model the aggregate job finding rate

[11] At this stage, we have not specified the order of our Taylor expansion. While our notation suggests a first-orderexpansion, this is done for clarity of exposition. In fact, as we will describe in the next section, we use a second-order approximation for all quantitative results.

$\lambda_t^{UE} \equiv \sum_{i=1}^{N} \omega_i \frac{u_i}{u} \lambda_{it}^{UE}$ with a matching function which allows us to interpret movements in job finding probability in terms of changes in hiring and changes in matching efficiency.[12]

Specifically, 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

$$m_t = m_{0t} U_t^{\sigma} V_t^{1-\sigma} \tag{6}$$

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.[13]

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

$$\ln \lambda_t^{UE} = \ln m_{0t} + (1 - \sigma) \ln \theta_t \tag{7}$$

with $\theta = \frac{v}{u}$ the aggregate labor market tightness, $u = U/LF$, $v = V/LF$ and LF the labor force.

In a standard Mortensen-Pissarides (1994) model, labor market tightness θ_t is pinned down by the job creation condition, i.e., vacancies are posted until the expected cost of hiring a worker equals the present discounted value of a match. Thus, the movements in λ_t^{UE} explained by movements in θ_t can be interpreted as changes in hiring. Movements in λ_t^{UE} due to movements in m_{0t} will be interpreted as changes in aggregate matching efficiency. A number of factors can affect m_{0t}: 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.[14]

Finally, to go back to (5) and use (7) to interpret movements in job finding rates, we use the fact that, in practice, the job finding rates of different demographic groups are highly

[12] Unlike typical estimates of the matching function, our aggregate job finding rate measure holds demographic shares constant.

[13] The Cobb-Douglas matching function is used in almost all macroeconomic models with search and search and matching frictions (e.g., Pissarides, 2001). Allowing for non constant returns to scale or using a more general CES matching function $m_t = m_{0t} \left[\sigma U_t^{\rho} + (1 - \sigma) V_t^{\rho}\right]^{1/\rho}$ gives very similar results.

[14] In Barnichon and Figura (2011), we present an empirical framework to study the determinants of aggregate matching efficiency movements over 1976-2010.

correlated so that $d\lambda_{it}^{UE} \simeq d\lambda_t^{UE}$.[15] We then write

$$\begin{aligned}\sum_{i=1}^{N} \omega_i \frac{u_i}{u} \alpha_i^{UE} d\lambda_{it}^{UE} &= \alpha^{UE} d\lambda_t^{UE} + \eta_t \\ &= \alpha^{UE} \lambda^{UE} \frac{dm_{0t}}{m_0} + \alpha^{UE} \lambda^{UE} (1-\sigma) \frac{d\theta_t}{\theta} + \eta_t \qquad (8)\end{aligned}$$

with $\alpha^{UE} = \sum_{i=1}^{N} \omega_i \frac{u_i}{u} \alpha_i^{UE}$ and $\eta_t = \sum_{i=1}^{N} \omega_i \frac{u_i}{u} \alpha_i^{UE} \left(d\lambda_{it}^{UE} - d\lambda_t^{UE} \right) \ll 1$.

3.2 Interpreting movements in the job separation rate

Movements in the job separation rate λ^{EU} can originate in two actions: a layoff or a quit. A layoff tends to be a decision of the firm, whereas a quit tends to be a decision of the worker. To interpret λ^{EU}, we will thus use micro data to refine our measure of separation and study instead separately λ^{EU^l} and λ^{EU^q} with $\lambda^{EU} = \lambda^{EU^l} + \lambda^{EU^q}$, with λ^{EU^l} the hazard rate of moving from employment to unemployment through a layoff and λ^{EU^q} the hazard rate of moving from employment to unemployment through a quit. We make this distinction for each demographic group i.

3.3 Interpreting movements in and out of the labor force

The last two terms in (4) are the contributions of movements in-and-out of the labor force to unemployment fluctuations. In this section, we argue that these movements depend on three factors: (i) firms' hiring policies, (ii) the propensity of active individuals to exit the labor force –labor force attachment–, and (iii) the composition of the pool of inactives (or Not-in-the-Labor-Force, NLF) and the presence of marginally attached individuals. In turn, we argue that the composition of the NLF is mainly driven by the propensity of inactive individuals to join or leave the labor market, defined as including any individual who wants a job.

3.3.1 Interpreting λ^{EI} and λ^{UI}: labor force exit

Movements in the hazard rates λ^{EI} and λ^{UI} capture changes in the propensity of individuals (employed or unemployed) to leave the labor force. Thus, movements in unemployment originating in λ^{EI} and λ^{UI} are driven by individuals' decision to exit the labor.

[15] Shimer (2007) and Elsby, Hobijn and Sahin (2010) report evidence supporting that hypothesis.

3.3.2 Interpreting $\lambda^{IE|ILF}$: hiring, composition of the NLF and labor market participation

To interpret $\lambda_t^{IE|ILF}$, we need to make a few assumptions to impose a little bit of structure on the problem. Importantly, we will be able to test our assumptions by verifying that our proposed decomposition explains most of the movements in $\lambda^{IE|ILF}$.

Note that $P(IE)$, the probability that an inactive individual finds a job, satisfies

$$P(IE) = P(ILF)P(IE|ILF) \tag{9}$$

with $P(ILF) = P(IE) + P(IU)$, the probability that an inactive individual joins the labor force, and $P(IE|ILF)$ the probability of finding a job conditional on having joined the labor force.

The latter, $P(IE|ILF) = \frac{\#IE}{\#IE+\#IU}$, is the fraction of inactive individuals who enter the labor force through employment, and is a function of job availability as well as the composition of the inactivity pool. First, $P(IE|ILF)$ captures the period job finding probability of labor force entrants with zero unemployment duration equal to zero. We thus posit that $P(IE|ILF)$ is related to $P(U^oE)$,the job finding probability of labor force entrants. And since, as shown in Shimer (2007) and Elsby, Michaels and Solon (2009), the job finding probabilities of the unemployed classified by unemployment reason (e.g., job losers, job leavers, labor force entrants, etc..) comove very closely together, we posit that $P(IE|ILF)$ is related to $P(UE)$ and thus to job availability and labor market tightness through the matching function. Second, time-varying differences in the composition of the inactivity pool and the composition of the unemployment pool can lead to time-varying differences between $P(IE|ILF)$ and $P(UE)$.

It is well known that the pool of inactive individuals is heterogeneous and contains a category of individuals, the marginally attached to the labor force –individuals that are not searching for a job but nonetheless want one–, that may behave differently from the "truly" inactive, –individuals who do not want a job and are indifferent to the state of the labor market–.[16] Because of such heterogeneity, changes in the fraction of marginally attached in the NLF pool may generate movements in $P(IE|ILF)$ unexplained by movements in $P(UE)$.

Denote I^U the number of NLF individuals who are marginally attached to the labor force, and I^I the number of "truly" inactive NLF individuals with $I^U + I^I = I$. We can then write

$$P(IE|ILF) = \frac{I^U}{I}P(I^UE|I^ULF) + \left(1 - \frac{I^U}{I}\right)P(I^IE|I^ILF). \tag{10}$$

If the presence of marginally attached individuals is the only important source of hetero-

[16] An individual is considered unemployed if he does not have a job *and* is actively looking for one.

geneity mattering for movements in $P(IE|ILF)$, we can then assume that the conditional job finding probability of marginally attached and truly inactive individuals can be both expressed as functions of $P(UE)$ only. To convert (9) and (10) in hazard rates, note that the period probability of transiting from A to B satisfies $P(AB) = 1 - e^{-\lambda^{AB}} \simeq \lambda^{AB}$ for λ^{AB} small, so that we can write $P(ILF) \simeq \lambda^{ILF}$ since $\lambda^{ILF} = \lambda^{IE} + \lambda^{IU}$ is small (and $< .1$), so that we can posit

$$\lambda^{IE} = \lambda^{ILF}\left(\frac{I^U}{I} f(\lambda^{UE}) + \left(1 - \frac{I^U}{I}\right) g(\lambda^{UE})\right) \tag{11}$$

with $f(.)$ and $g(.)$ some functions to be determined.

Importantly, we will be able to test the validity of our assumptions by verifying that our decomposition explains most of the movements in $\lambda^{IE|ILF}$.

To interpret movements in $\frac{\lambda^{IE}}{\lambda^{ILF}}$, we log-linearize (11) and estimate the regression

$$\ln \frac{\lambda_t^{IE}}{\lambda_t^{ILF}} = a_0 + a_1 \ln \lambda_t^{UE} + a_2 \ln \frac{I_t^U}{I_t} + \varepsilon_t. \tag{12}$$

Using (12), we can then decompose movements in $\frac{\lambda_t^{IE}}{\lambda_t^{ILF}}$ into: (i) changes in hiring and (ii) changes in the fraction of inactive individuals who want a job.[17]

While knowing the extent to which the composition of the inactivity pool matters for unemployment is interesting, we would like to know the forces behind movements in $\frac{I_t^U}{I_t}$.[18] Just like for the unemployment rate, we can decompose the stock $\frac{I^U}{I}$ into the contributions of its flows. To do so, we need to split the labor market state "inactivity" into two states: truly inactive and marginally attached. That way, we can express $\frac{I^U}{I}$ as a functions of 12 hazard rates.[19] While this decomposition can appear to be cumbersome, we will show that in practice only two hazard rates matter for $\frac{I^U}{I}$; $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$, so that

$$d \ln \frac{I_t^U}{I_t} = \beta^{I^U I^I} d \ln \lambda_t^{I^U I^I} + \beta^{I^I I^U} d \ln \lambda_t^{I^I I^U} + \kappa_t \tag{13}$$

with κ_t small.

Importantly, these two hazard rates have a clear interpretation: they correspond to the propensity of inactive individuals to join or leave the labor market (defined as "individuals

[17] Of course, this interpretation is informative if the residual ε_t is small, which, as we will see, is the case in practice.

[18] Indeed, movements in $\frac{I^U}{I}$ could arise out of a pure composition effect (e.g., if unemployed have the highest propensity to become marginally attached and if unemployment goes down) or because more marginally attached give up with the labor market and stop wanting a job.

[19] Because of data limitation, such a decomposition is only possible after 1994. Fortunately, as we will see in the empirical section, $\frac{I^U}{I}$ contributes little to unemployment fluctuations before the mid-90s.

who want a job"), i.e., to changes in the economy's total labor supply. Movements in $\frac{I^U}{I}$ can thus be seen as changes in labor supply. Alternatively, we can interpret (ii) as movements in the average attachment of the inactives to the labor market. As we will see empirically, the more attached to the labor market are inactives (on average), the higher is the unemployment rate because inactive individuals who are more attached to the labor force are more likely to join the unemployment pool and raise unemployment.

3.4 A level decomposition of the unemployment rate

By taking a second-order Taylor expansion of (3) and (4) around the mean of the hazard rates, we can decompose movements in the level of unemployment using[20]

$$\begin{aligned} du_t^{ss} &= \alpha^{demog} du_t^{demog} + \alpha^{UE} du_t^{hiring} + \alpha^{EU} du_t^{layoff} + \alpha^{EU} du_t^{quit} \\ &\quad + \alpha^{LF-I} du_t^{LF-I} + \alpha^{\frac{I^U}{I}} du_t^{\frac{I^U}{I}} + \alpha^{UE} du_t^{m_0} + \mu_t \end{aligned} \tag{14}$$

with du_t^{XX} capturing the changes in unemployment due, respectively, to changes in hiring, layoffs, quits, labor force entry, labor force attachment and matching efficiency holding demographics constant. The error term μ_t captures mostly the movements in ε_t –the movements in λ_t^{IE} not explained by λ_t^{UE} or $\frac{I_t^U}{I_t}$, as well as the (in practice) negligible movements in η_t, and the small 2^{nd}-order approximation error.

Thanks to this linear decomposition, we can then assess the separate contributions of each economic concept by noting as Fujita and Ramey (2009) that

$$Var\,(A + B) = Cov(A, A + B) + Cov(B, A + B) \tag{15}$$

with $A, B \in \mathbb{R}$ so that, for example, $\frac{Cov(du_t^{hiring}, du_t^{ss})}{var(du_t^{ss})}$ measures the fraction of unemployment's variance due to changes in hiring.

[20] By taking a Taylor expansion around the mean, instead of around an HP-filter trend or around last period's value as in Elsby et al. (2009) or Fujita and Ramey (2009), our decomposition has the advantage of covering all frequencies. To guarantee that the approximation remains good however, we take a second-order approximation, which performs extremely well, as we will see in Figure 1. The expressions for the first- and second-order coefficients are shown in the Appendix.

4 Estimation

4.1 Measuring individuals' transition rates

To identify the individuals' transition probabilities, we use matched CPS micro data to measure the number of workers moving from state $A \in S$ to state $B \in S$ each month.[21] The estimated transition probabilities are biased because of a time-aggregation bias due to the fact that one can only observe transitions at discrete (in this case, monthly) intervals (Shimer, 2007). We thus correct for time-aggregation bias for each demographic group. Moreover, since different categories of unemployed (e.g., job losers versus job quitters, (Elsby, Michaels and Solon, 2009)) have very different levels of job finding rate, this leads to different extent of time-aggregation bias for the transitions involving job losers and job quitters (in particular, the E-U^l and the E-U^q transitions). Not taking this into account could lead to erroneous corrections for E-U^l and the E-U^q. Extending Shimer (2007), we thus consider a 5-states model that takes into account the reason for unemployment, and we classify jobless workers according to the event that led to their unemployment status: a layoff l, a quit q and a labor force entrance o.[22] 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 5 possible states with $S = \{U^l, U^q, U^o, E, I\}$. To correct for the 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:[23]

$$\dot{n}_t^{AB}(\tau) = \sum_{C \neq B} n_t^{AC}(\tau)\lambda_t^{CB} - n_t^{AB}(\tau) \sum_{C \neq B} \lambda_t^{BC}, \qquad \forall\ A \neq B. \tag{16}$$

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

[21] As described in the Appendix., we adjust the transition probabilities for the 1994 CPS redesign

[22] 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).

[23] 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, $\lambda^{lU^q} = 0$, $\lambda^{IU^l} = 0$, etc..)

the monthly series.

4.2 Estimating a matching function

We estimate a matching function by regressing

$$\ln \lambda_t^{UE} = (1-\sigma)\ln \theta_t + \ln m_0 + \varepsilon_t \tag{17}$$

using our measure of the job finding rate λ^{UE} as the dependent variable. With $\ln m_0$ the intercept of the regression, aggregate matching efficiency is then given by

$$\ln m_{0t} = \ln m_0 + \varepsilon_t. \tag{18}$$

We estimate (17) with monthly data using the composite help-wanted index presented in Barnichon (2010) as a proxy for vacancy posting.[24] 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. With an R^2 of 0.85, movements in labor market tightness explain a large fraction of movements in the job finding rate.

4.3 Estimating the labor force entry rate of inactive individuals

To interpret $\lambda^{IE|ILF}$ in terms of hiring and attachment of the inactives to the labor force, we proceed as described in Section 2 and estimate

$$\ln \frac{\lambda_t^{IE}}{\lambda_t^{ILF}} = a_0 + a_1 \ln \lambda_t^{UE} + a_2 \ln \frac{I_t^U}{I_t} + \varepsilon_t.$$

To obtain a measure of $\frac{I_t^U}{I_t}$ over 1976:Q1-2009:Q4, we classify as "marginally attached" inactive individuals who respond yes or maybe to the question "Do you currently want a job now, either full or part-time?".[25] Column (3) of Table 1 presents the results of the regres-

[24] 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.

[25] Importantly, the phrasing of the question changed very little over 1976-2010, allowing us to estimate a time-series of $\frac{I_t^U}{I_t}$ over the whole sample. However, prior to 1994, the question was only asked to the outgoing rotation groups, thus preventing us from estimating the transition rates in and out of the states I^U and I^I. We

sions estimated over 1976-2009. Both λ^{UE} and $\frac{I^U}{I}$ come out highly significantly, but most importantly for our purpose of interpreting movements in $\lambda^{IE|ILF}$, movements in λ^{UE} and $\frac{I^U}{I}$ explain 85% percent of the variance of $\lambda^{IE|ILF}$.[26]

Note that a_2 is negative, implying that an increase in the share of marginally attached individuals reduces the average conditional job finding probability of an inactive joining the labor force, and thus increases the unemployment rate. To understand why, it is instructive to compare the magnitude of the transition probabilities out of inactivity for the truly inactives and the marginally attached. Although marginally attached have a higher (about 3 times larger) propensity to find a job than inactive individuals, they also have an even higher (about 10 times larger) propensity to join the unemployment pool. As a result, the conditional probability of finding a job for an inactive $P(IE|ILF)$ is larger for a truly inactive than for a marginally attached, and a higher fraction of marginally attached raises the unemployment rate.

5 An empirical decomposition of unemployment fluctuations

5.1 The main components of unemployment fluctuations

In this section, we use (14) to decompose unemployment rate fluctuations into the contributions of six components: hiring, layoff, quit, labor force exit, attachment of the inactives to the labor force and demographics. To summarize our results graphically, we group these margins of adjustment under the headings "firm-driven" (hiring and layoff) and "worker-driven" (quit, labor force exit, composition of the inactivity pool, and demographics).

Figure 1 plots steady-state unemployment along with its worker-driven component and illustrates our first main result: the secular trend in unemployment appears to be driven by workers' decisions and demographics, while the cyclical component of unemployment appears to be mainly driven by other factors, i.e., hiring and layoff. A variance decomposition using (14) confirms this impression, and Table 3 shows that 90% of the trend in unemployment since 1976 is the result of changes in demographics, labor market participation decisions and quits.[27] In contrast, about 90% of unemployment cyclical fluctuations are the result of hiring and layoff (excluding movements due to changes in matching efficiency).

return to that issue in Section YY where we estimate such transition rates over 1994-2010 in order to interpret the forces driving movements in $\frac{I_t^U}{I_t}$.

[26] While we report results for the aggregate hazard rates, the decomposition presented in the paper is built using separate regressions for each group.

[27] 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.

With an average contribution of 10 percent, changes in matching efficiency have, a non-trivial impact on the equilibrium unemployment rate. Moreover, Figure 2 shows that matching efficiency can decline substantially in recessions, as in the aftermath of the 1982 unemployment peak and during the 2008-2009 recession. Without any loss in matching efficiency, unemployment would have been about 60 basis points lower in 1984 and about 150 basis points lower in end 2010.

Studying the components in more details, Figure 2 presents the contributions of hiring, layoff and matching efficiency, and Figure 3 presents the contributions of quit, labor force entry and labor force exit as well as demographics. To present the results, we discuss low frequencies and business cycle frequencies separately.

5.2 Low frequencies

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, Bleakley and Fuhrer 1997, 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). In addition, labor demand based explanations have also been suggested, such as increasing wage flexibility (Davis, Faberman and Haltiwanger, 2006) or declining intensity of idiosyncratic labor demand shocks (Davis, Faberman, Haltiwanger, Jarmin and Miranda, 2010), which would reduce the use of the separation margin. However, absent an accounting framework to encompass all these hypotheses, there was no consensus on the quantitative role played by each explanation.

Our accounting framework allows us to quantify the contribution of each factor and also suggests a new possible explanation for unemployment's trend: a change in the composition of the inactivity pool, as the fraction of marginally attached individuals in the inactivity pool affects the unemployment rate.

Figure 3 shows that the trend in unemployment is due to three forces: changes in demographics (du_t^{demog}), a decline in the share of marginally attached individuals in the inactivity pool ($du_t^{\frac{I^U}{I}}$), and changes in labor force attachment of workers inside the labor force in the first half of the sample (du_t^{LF-I}). Together, these three factors lowered unemployment by about 2 ppt since 1976.

Table 3 confirms this visual inspection, and the three factors explain virtually all of the trend in unemployment. In units of unemployment rate, demographics lowered the unemployment rate by about 1ppt over 1976-2009, changes in labor force attachment lowered the unemployment rate by about 1/2ppt until the mid-90s before reverting these gains, and changes in the composition of the inactivity pool and a downward trend in the fraction of marginally-attached individuals lowered the unemployment rate by about 3/4ppt after the mid-90s. After controlling for demographic changes, the component of unemployment driven by hiring and layoff shows little evidence of a trend (Figure 2), and Table 3 confirms that hiring and layoff only account for a small fraction of unemployment low-frequency movements.[28]

To better understand movements in $\frac{I^U}{I}$, given the major, and unexplored, role played by marginally attached individuals in explaining the trend in unemployment after the mid-90s, we decompose the movements in $\frac{I^U}{I}$ into the flows in and out $\frac{I^U}{I}$ as described in (13) and similarly to our unemployment decomposition (14).[29] Table 2 shows that the trend in $\frac{I^U}{I}$ is due to two factors: a decline in the propensity of the truly inactive to want a job (movements in $\lambda^{I^I I^U}$) and join the labor market, defined as including any individual who wants a job, and an increase in the propensity of the marginally attached to give up any interest in working (movements in $\lambda^{I^U I^I}$). Movements in $\frac{I^U}{I}$ thus appear to be driven by individuals' decisions to leave or join the labor market, and one can interpret the trend in $\frac{I^U}{I}$ as capturing a progressive decline in "labor supply", although of a broader kind than the one implied by the traditional notion of a "labor force".

5.3 Business cycle frequencies

Turning to business cycle frequencies, Table 3 shows that firms' hiring and layoff policies are the two main determinants of unemployment fluctuations and account for respectively 52 and 37 percent of the cyclical fluctuations in unemployment. Labor force attachment and the share of marginally attached individuals do exhibit cyclical fluctuations but their contribution to unemployment fluctuations are small. As shown in Figure 3, in recessions, individuals have a stronger attachment to the labor force, which exacerbates unemployment fluctuations. The fraction of marginally attached individuals also tends to increase in the aftermath of recessions, possibly caused by an increase in the number of discouraged unemployed workers who give up looking for work. This also exacerbates unemployment fluctuations. In contrast, quits tame

[28] The absence of a trend in the unemployment inflow rate for job losers is not in contradiction with the existence of a secular trend in the unemployment inflow rate s_t (see Shimer (2007) or Figure A1 of the online Appendix). As can be seen in the online Appendix, part of the trend in the unemployment inflow rate is due to movements in and out of the labor force (the lower panel of Figure A3), a topic to which we turn next. The fraction of the trend in s_t coming from λ_t^{EU} (the upper-panel of Figure A3) is due to the aging of the baby boom (that we control for in Figure 2) and to the existence of a trend in quits to unemployment that we discuss below. Finally, and confirming our result, the job loser unemployment inflow rate constructed by Elsby, Michaels and Solon (2009) from unemployment duration data and reported in their Figure 9 also displays little evidence of a trend over 1976-2004.

[29] Because of a limitation in the CPS (Footnote GGG), transitions in-and-out of states I^U and I^I can only be measured after 1994. Our decomposition thus only covers 1994-2009.

unemployment fluctuations, as workers are less likely to quit in recession.[30] Overall, the cyclical contribution of the worker-driven component is small compared to that of hiring and layoff.

6 Heterogeneity and demographics

To better understand the movements in the various components of unemployment highlighted in (14), we now decompose each component into the separate contribution of the four main demographic groups: Prime-age male 25-55, Prime-age female 25-55, Younger than 25 and Over 55.

Considering separately the behaviors of the different demographic groups yields interesting insights. In particular, at low frequencies, trends in the worker-driven component (and therefore the trend in unemployment) can be attributed to changes in labor market participation decisions of prime-age females and young individuals. In contrast, changes in the labor force participation of prime-age males and old workers have had a relatively small effect on the trend in unemployment.

6.1 The trends in unemployment

We first study low-frequencies. Figure 4 decomposes the movements in du_t^{demog} plotted in Figure 3 into the contributions of four demographic groups: Prime-age male, Prime-age female, Younger than 25 and Older than 55. 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 higher unemployment rate than men. However, because young workers have a much higher average unemployment rate than prime age females, the effect of demographics is mostly driven by the declining share of young workers.

To explore the factors behind the trends in du_t^{I-LF} and $du_t^{\frac{I^U}{I}}$, Figure 5 and 6 decompose the movements in du_t^{I-LF} and $du_t^{\frac{I^U}{I}}$ plotted in Figure 3 into the contributions of the same four demographic groups, and Table 4 provides variance decompositions of the contribution of each demographic group to movements in du_t^{I-LF} and $du_t^{\frac{I^U}{I}}$.

[30] This is in line with the observation made by Akerlof et al. (1998) and Elsby, Michaels and Solon (2009), among others, that quits are procyclical while layoffs are countercyclical.

Up until the early to mid 90s, and aside from the contribution of demographics, the trend in unemployment owes to changes in labor force attachment. The main factor behind the trend in du_t^{LF-I} is the change in prime-age females and young workers attachment to the labor force with women and young workers respectively accounting for about 50% and 30% of the trend (Table 3).[31]

Since the mid 90s, the downward trend in unemployment owes to a downward trend in the share of marginally attached individuals in the inactivity pool. This trend can be observed for all demographics groups except for older workers and is most pronounced (and having started earlier) for young individuals. Moreover, the *effect* of these trends on unemployment is especially strong amongst young workers since the early 2000s because of youngs' high average unemployment. As a result, while young workers represent only 18% of the labor force, they account for 46% of the trend in unemployment coming from labor force entry (Table 3). In contrast, because of their low average unemployment, the contribution of old workers and prime-age male is relatively small compared to their labor force share.[32]

Interestingly, since the mid-90s, all demographic groups *inside* the labor force have also displayed a decline in their attachment to the labor force, which raised unemployment.

Finally, the contribution of quits to the trend in unemployment comes overwhelmingly from young workers, accounting for 60% of the contribution of du_t^{quit}.

6.2 The cycles in unemployment

To decompose the contributions of different demographic groups to fluctuations in aggregate unemployment, Table 4 reproduces Table 3 but at business cycle frequencies. In addition, to study whether a given adjustment margin plays a more or less prevalent role across different groups, we apply our accounting decomposition (14) to the unemployment rate of each demographic group, and Table 4b presents the results of the corresponding variance decompositions.

Starting with job separation, layoffs and quits play different roles across demographic groups. Quits play a small role for prime-age males but are much more important for young

[31] Digging further, the Appendix shows the U-I and E-I transition behind the LF-I transitions and reveals a different pattern for prime age females and young workers up until the mid-90s. For prime-age females, the trend in LF-I comes from the hazard rates λ^{EI} and λ^{UI} converging towards those of men until the early 90s, as emphasized by Abraham and Shimer (2001). In contrast, young workers experienced little trend in their E-I transition rate but a continuous upward trend in their U-I transition rate since the mid-70s, consistent with more time spent in school. Importantly, the trend in UI for young workers is present for both men and women. See Aaronson et al. (2006) and Aaronson, Park and Sullivan (2006) for discussions of the factors behind the decline in youths' labor force participation rate.

[32] This explains why notable changes in the labor force participation of prime-age males, in particular the declining labor force participation rate of prime-age male documented by Juhn, Murphy and Topel (1991)–, have had a very small quantitative effect on the unemployment rate.

workers, while the picture is reversed for layoffs (Table 4b).[33] As a result, while more than 50% of the contribution of quits to the variance of aggregate unemployment is due to young workers (Table 4), more than 50% of the contribution of layoffs to the variance of aggregate unemployment is due prime-age males.

Both labor force attachment and the fraction of marginally attached tend to be countercyclical for all groups (Figure 5 and 6).[34] Nonetheless, as shown in Table 4b, these two aspects of labor market participation play a much bigger role for the unemployment rate of young and old individuals and prime-age females. For instance, the labor force exit decision is important to understand old workers unemployment rate (and this is probably linked to their retirement decision), but plays only a small role for young individuals. In a similar vein, movements in the share of inactives who want a job plays a marginal role for prime-age individuals, but is much more important for old individuals or prime-age females. These findings are consistent with the common view that these demographic groups exhibit a more elastic labor supply than prime-age males.[35]

7 Theoretical implications

Low-frequency movements: At low-frequencies, we found that, over 1976-2009, the trend in the unemployment inflow rate $s_t = \lambda_t^{EU} + \frac{\lambda_t^{EI}\lambda_t^{IU}}{\lambda_t^{IU}+\lambda_t^{IE}}$ is caused by secular changes in demographics and in labor force attachment of the actives and inactives. In contrast, the layoff rate to unemployment displays no trend. Using Elsby, Hobijn and Sahin's (2010) finding that almost all (about 90 percent over 2001-2009) of laid-off workers end up in the unemployment pool (instead of directly getting another job or leaving the labor force), the absence of a trend in the layoff rate to unemployment suggest that the layoff rate also displays little trend over 1976-2009.[36] This has a number of implications. Davis, Faberman, Haltiwanger, Jarmin and

[33] See also the Appendix where we decompose the movements in du_t^{layoff} and du_t^{quit} plotted in Figure 3 into the contributions of the same four demographic groups as in Figure 4 and 5.

[34] However, looking more carefully, heterogeneity is again prevalent. The countercyclicality of labor force attachment occurs through two channels; E-I transitions and U-I transistions. In recessions, workers are less likely to leave their job and the labor force and are also less likely to stop searching for a job and leave the labor. While the first effect lowers the unemployment rate in recessions, the second effect increases unemployment in recessions. As shown in Figures 5 and GG in the Appendix, the second effect dominates for all demographic groups except for young workers. For young workers, the effect of E-I is stronger than in the case of other groups and labor force attachment sometimes lowers unemployment in recessions (as in the Great Recession).

[35] As prime-age males are the main income earners in many households, they display a relatively inelastic labor supply. Labor market parcipation could be a lot more elastic for prime-age women and old individuals through an added-worker effect (in which spouses of individuals who lost their job in the recession decide to join the labor force in search of additional income) or through a wealth-effect (in which a dramatic drop in the wealth of young retirees (through a stock-market crash) lead them to reenter the labor force).

[36] For this reasoning to work, we must assume that Elsby et al.'s finding over 2001-2009 holds over the whole sample period 1976-2009.

Miranda (2010) link the secular decline in the unemployment inflow rate to the secular decline in the job destruction rate. The absence of a trend in the layoff rate and the fact that we can attribute all of the decline in s_t to changes in demographics and workers' behavior suggest that the secular decline in job destruction may be related to changes in demographics and workers' behavior. Davis et al. (2010) also link the 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. Again, the absence of a trend in the layoff rate would suggest that workers' behavior played an important role. 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. This possibility is in line with the recent work of Jaimovich and Siu (2009) who find that the aging of the labor force accounts for a significant fraction of the decline in postwar business cycle volatility since the late 70s. In particular, their finding that young workers have the strongest effect on output and employment cyclical volatility is consistent with the higher turn-over of young workers.

In contrast, labor demand based explanations, 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 to unemployment, as the micro evidence (Davis, Faberman and Haltiwanger, 2010) suggests that a decrease in the variance of idiosyncratic shocks leads to a lower job destruction rate and a lower layoff rate.

Business cycle fluctuations: In the Mortensen-Pissarides (1994) search and matching model, the canonical model of equilibrium unemployment, unemployment fluctuations are driven by changes in job posting and job separation, consistent with our finding that hiring and layoff account for a large fraction of unemployment's variance. However, the non-trivial contribution of labor force attachment and the role of marginally attached individuals, whose share increases in weak labor markets, call for a better understanding of the forces driving individuals decisions to want a job, look for one or stay inactive.[37] Moreover, these labor market participation decisions play a bigger role for prime-age females and young individuals, highlighting the fact that the unemployment rate is driven by the decisions of heterogeneous individuals and cautioning against systematically assuming homogenous agents when studying unemployment. Similarly, we found that the relative importance of quits and layoffs differ across demographic groups. While, in the Mortensen-Pissarides model, quits and layoffs are indistinguishable since a match terminates when it is jointly optimal for both parties to separate, this result shows that understanding theoretically the quit-layoff distinction is an important

[37] See Garibaldi and Wasmer (2005), Haefke and Reiter (2006), Campolmi and Gnocchi (2010), Gali (2010), Krussel, Mukoyama, Rogerson and Sahin (2011a,2011b) for recent efforts in introducing a labor force participation decision.

goal for future research (see e.g. McLaughlin, 1991) and echoes the point made by Davis (2006).

Finally, while shocks to matching efficiency are rarely considered in search models, understanding and modeling the factors behind the non-trivial matching efficiency movements (Figure 2) is an interesting question for future research (Justiniano and Michelacci 2010, Barnichon and Figura 2011, Furlanetto and Groshenny 2011).

8 The Beveridge curve

An empirical relationship that has attracted a lot of interest in the literature and in policy circles is the Beveridge curve, the downward sloping relation between unemployment and vacancy posting. Since the influential works of Abraham and Katz (1986) and Blanchard and Diamond (1989), the Beveridge curve is known to contain essential information about the functioning of the labor market 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 diverse factors, from cyclical factors, such as changes in the intensity of layoffs, to structural factors, such as demographic changes or changes in matching efficiency.

It is now instructive to restate some of our results in Beveridge curve space and revisit the behavior of the empirical Beveridge curve –the empirical U-V locus– over 1976-2009 (Figure 7) in light of our findings. We examine three questions that received some attention in the literature and in the policy debate (Pissarides 1985, Valletta 2005, Tasci and Lindner, 2010): (i) Why did the U-V locus progressively shift to the left since 1976?, (ii) why did the Beveridge curve shifted so strongly in the 2008-2009 recession, and (iii) Why does the U-V locus curve exhibit counter-clockwise loops during recessions?

8.1 The empirical Beveridge curve

As a preliminary step, it is important to contrast the observed –empirical– Beveridge curve to the theoretical Beveridge curve that emerges in the steady-state of search and matching models (Pissarides, 1985) or, similarly, in our steady-state decomposition (14) based on the existence of a matching function.

Empirically, the Beveridge curve is the downward sloping relation between unemployment and vacancy, or

$$u_t = f(\theta_t, \varepsilon_t)$$

with $\frac{\partial f(\theta,\varepsilon)}{\partial \theta} < 0$ and where ε denotes shifts of the Beveridge curve.

Our decomposition (14) implies a Beveridge curve since, by definition, $du_t^{hiring} = du_t^{hiring}(\theta_t)$, so that we have

$$\begin{aligned} du_t^{ss} &= \alpha^{demog} du_t^{demog} + \alpha^{UE} du_t^{hiring}(\theta_t) + \alpha^{EU} du_t^{layoff} + \alpha^{EU} du_t^{quit} \\ &\quad + \alpha^{LF-I} du_t^{LF-I} + \alpha^{\frac{I^U}{I}} du_t^{\frac{I^U}{I}} + \alpha^{UE} du_t^{m_0} + \mu_t. \end{aligned} \tag{19}$$

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 (19) as firms adjust vacancies in response to economic conditions. Changes in firms' labor demand translates into movements in θ_t, i.e. movements along the Beveridge curve.

As (19) shows, in theory, the Beveridge curve can shift for different reasons: changes in the intensity of layoffs (du_t^{layoff}) and quits (du_t^{quit}), changes in the efficiency of matching workers to jobs. ($du_t^{m_0}$), etc...[38]

Empirically however, one need to distinguish "usual" from "unusual" movements in those "natural shifters" of the Beveridge curve. Since the observed (empirical) Beveridge curve captures all movements in u_t correlated with θ_t (from $u_t = f(\theta_t,\varepsilon_t)$), movements in those shifters will shift the empirical Beveridge only if they are "unusual" given the movements in θ_t.[39]

To capture such unusual changes, and hence the shifts in the empirical Beveridge curve due the different components of unemployment, we regress each element of u_t^{ss} on θ_t

$$du_t^{XX} = a + bd\ln\theta_t + \varepsilon_t^{XX}$$

with $XX = \{demog, layoff, quit, LF\_I, I^U/I, m_0\}$. Collecting all the ε_t^{XX} together, we then get the total shifts in the BC as well as its subcomponents.

8.2 Why did the U-V locus progressively shift to the left since 1976?

By isolating the worker-driven component of Beveridge curve shifts, we can visualize the progressive leftward shift of the empirical Beveridge curve caused by the effect of demographics and changes in workers' behavior. Figure 8 plots the shifts in the empirical U-V locus generated by changes in demographics, quit and labor market participation decisions. The secular

[38] Similarly, in the Pissarides (1985) model, changes in the exogenous job separation rate s shift the theoretical Beveridge curve $u = \frac{s}{s+f(\theta)}$.

[39] Unusual in the sense that their movements cannot be explained by the movements in θ_t.

leftward shift is clearly apparent. Given the absence of a trend in the other Beveridge curve shifters (the layoff rate and matching efficiency), we conclude that the secular shift in the empirical Beveridge curve over the last 35 years is due entirely to changes in demographics and labor market participation decisions.

8.3 Why did the Beveridge curve shift dramatically in the 2008-2009 recession?

Proceeding in a similar fashion, Figure (8) decomposes the dramatic shift over 2006-2010 into its subcomponents. First (dashed black line), we exclude shifts coming from layoffs, quits, I^U/I, and matching efficiency and find no evidence of a shift. Second (dashed grey line), we add shifts coming from layoffs, and find that these two factors explain about a third of the shift. Finally, matching efficiency explains the other two-thirds. We thus conclude that the exceptional shift in the Beveridge curve owes to an usually large increase in layoffs and an exceptional decline in matching efficiency (see Barnichon and Figura, 2010).

8.3.1 Counter-clockwise looping

A well-known characteristic of the empirical Beveridge curve is its tendency to draw counter-clockwise loops during recessions (Figure 7) with vacancies adjusting in advance of unemployment. As shown in Pissarides (1985), an explanation for such counter-clockwise loops is that vacancies adjust quickly, but that, in recessions, unemployment adjusts only sluggishly towards its equilibrium (i.e., steady-state) level. In other words, unemployment may not adjust instantaneously to its steady state, and out-of-steady state dynamics matter.

Our framework provides a simple way to test this hypothesis. The theoretical Beveridge curve implied by (19) is built on the assumption of unemployment being in steady-state. Thus, if out-of-steady-states are indeed behind the looping, our theoretical Beveridge curve should display no looping. Figure 9 plots u_t implied by (19) along with vacancy posting, and shows that this is exactly the case; there is no looping.[40] To our knowledge, this empirical confirmation of Pissarides' hypothesis had not been made before.

9 Conclusion

This paper presents an accounting framework to decompose unemployment fluctuations at all frequencies into the contributions of demographics and the economic decisions: hiring (or job

[40] The looping in the early-80s is clockwise, unrelated to out-of-steady-state dynamics, while looping in counter-clockwise in the empirical Beveridge curve.

creation), layoff, quit, and labor market participation decisions. At business cycle frequencies, hiring and layoffs appear as the main determinants of unemployment fluctuations, consistent with standard business cycle models of the labor market (Mortensen-Pissarides, 1994). At low frequencies, most of the downward trend in unemployment since the mid-70s can be attributed to the aging of the baby boom and downward trends in labor force entry and exit, but not to trends in hiring and layoffs. However, this aggregate result masks important differences across demographic groups, with labor force participation decisions playing a more important role for young, old and prime-age females at any frequency.

We conclude our paper by showing that the gradual leftward shift of the empirical Beveridge curve over the last 40 years owes to demographic factors and labor force participation, but not to improvements in the efficiency of the matching process or to changes in firms' hiring and layoff policies.

Our unemployment accounting framework can be easily applied to other countries where vacancy data and labor force surveys data are available, such as Japan, the UK or France. In addition to studying the forces driving unemployment fluctuations, it would be interesting to study how the cyclicality of the labor force participation decision varies across countries with different welfare systems. At low frequencies, exploring the sources of the trends in unemployment would be a particularly interesting project because the US, Japan, the UK and France are characterized by different labor market institutions and experienced different secular trends in their unemployment rate and unemployment flows (Rogerson and Shimer, 2010).

Appendix

A second-order decomposition

Recall that

$$u_t^{ss} = \frac{s_t}{s_t + f_t} \tag{20}$$

with s_t and f_t defined by

$$\begin{cases} s_t = \lambda_t^{EU} + \lambda_t^{EI}\lambda_t^{IE|ILF} \\ f_t = \lambda_t^{UE} + \lambda_t^{UI}\left(1 - \lambda_t^{IE|ILF}\right) \end{cases}.$$

A second-order Taylor expansion of (20) around the mean of λ_t^{EU}, λ_t^{UE}, λ_t^{EI}, λ_t^{UI} and $\lambda_t^{IE|ILF}$ gives us the first order terms:

$$\begin{aligned}
\beta^{UE} &= -\frac{\left(\lambda^{El} + \lambda^{Eq} - \lambda^{EI}(\lambda^{IUE} - 1)\right)}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}(\lambda^{IUE} - 1))^2} \\
\beta^{EU} &= \frac{\lambda^{UE} + \lambda^{IUE}\lambda^{UI}}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}(\lambda^{IUE} - 1))^2} \\
\beta^{EI} &= -\frac{-(\lambda^{IUE} - 1)(\lambda^{UE} + \lambda^{IUE}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}\lambda^{IUE})^2} \\
\beta^{UI} &= -\frac{-\lambda^{IUE}(\lambda^{El} + \lambda^{Eq} + -\lambda^{EI}(\lambda^{IUE} - 1))}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}(\lambda^{IUE} - 1))^2} \\
\beta^{IUE} &= -\frac{-\lambda^{UI}(\lambda^{El} + \lambda^{Eq}) + \lambda^{EI}(\lambda^{UE} + \lambda^{UI}))}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}\lambda^{IUE})^2}
\end{aligned}$$

the second-order terms

$$\begin{aligned}
\beta_2^{UE} &= \frac{2\left(\lambda^{El} + \lambda^{Eq} - \lambda^{EI}(\lambda^{IUE} - 1)\right)}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}(\lambda^{IUE} - 1))^3} \\
\beta_2^{EU} &= -\frac{2(\lambda^{UE} + \lambda^{IUE}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}\lambda^{IUE})^3} \\
\beta_2^{EI} &= -\frac{-2(\lambda^{IUE} - 1)^2(\lambda^{UE} + \lambda^{IUE}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}\lambda^{IUE})^3} \\
\beta_2^{UI} &= \frac{2(\lambda^{IUE})^2(\lambda^{El} + \lambda^{Eq} - \lambda^{EI}(\lambda^{IUE} - 1))}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}(\lambda^{IUE} - 1))^3} \\
\beta_2^{IUE} &= -\frac{-2(\lambda^{EI} - \lambda^{UI})(\lambda^{EI}\lambda^{UE} + \lambda^{EI}\lambda^{UI} + \lambda^{El}\lambda^{UI} + \lambda^{Eq}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IUE}\lambda^{UI} - \lambda^{EI}\lambda^{IUE})^3}
\end{aligned}$$

and the cross-order term (available upon request), so that with

$$du_t = \sum \beta^{AB}(\lambda_t^{AB} - \overline{\lambda^{AB}}) + \sum_{A \neq B} \frac{\beta_2^{AB}}{2}(\lambda_t^{AB} - \overline{\lambda^{AB}})^2 + \textit{cross-order terms} + \eta_t$$

with $AB \in \{UE, EU, UI, EI, IUE\}$

Decomposing $\lambda_t^{IE|ILF}$ into the contributions of λ_t^{UE} and $\frac{I_t^U}{I_t}$,.and λ_t^{UE} into the contributions of θ_t and m_{0t} using (12) and (8), we can decompose du_t according to (14).

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) that we multiply by the average growth rate of the transition probability over 1994m1-2009. That 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.

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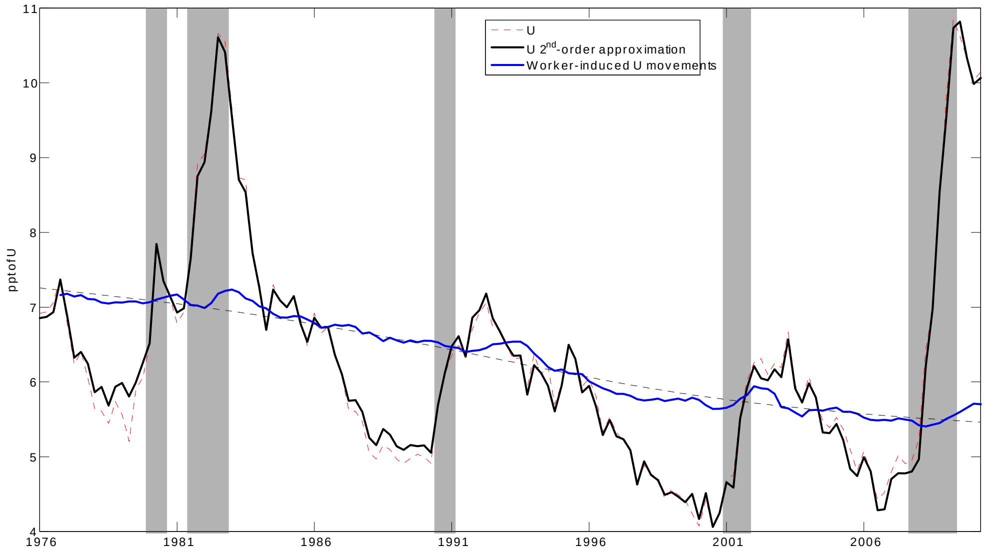

Figure 1: Steady-state unemployment (dashed red line), approximated unemployment from 2^{nd}order Taylor expansion (black line), and unemployment movements explained by demographics, entry/exit from the labor force and quits (blue line, labelled "worker-induced unemployment movements"). For illustration, the dashed black line corresponds the trend obtained from an HP-filter with $\lambda = 10^7$.

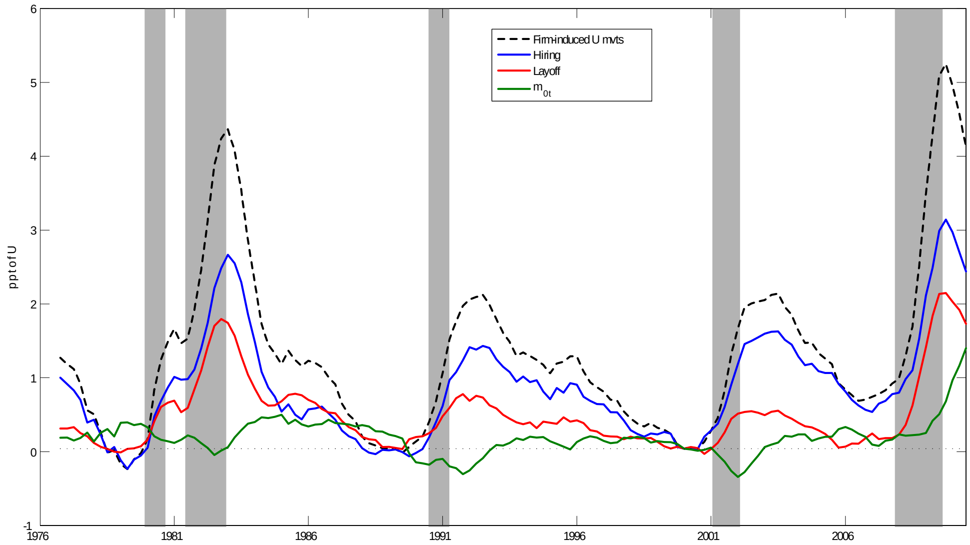

Figure 2: Decomposition of firm-induced unemployment movements into the contributions of hiring, layoffs and changes in matching efficiency, 1976-2010. The plotted series are 4-quarter moving averages.

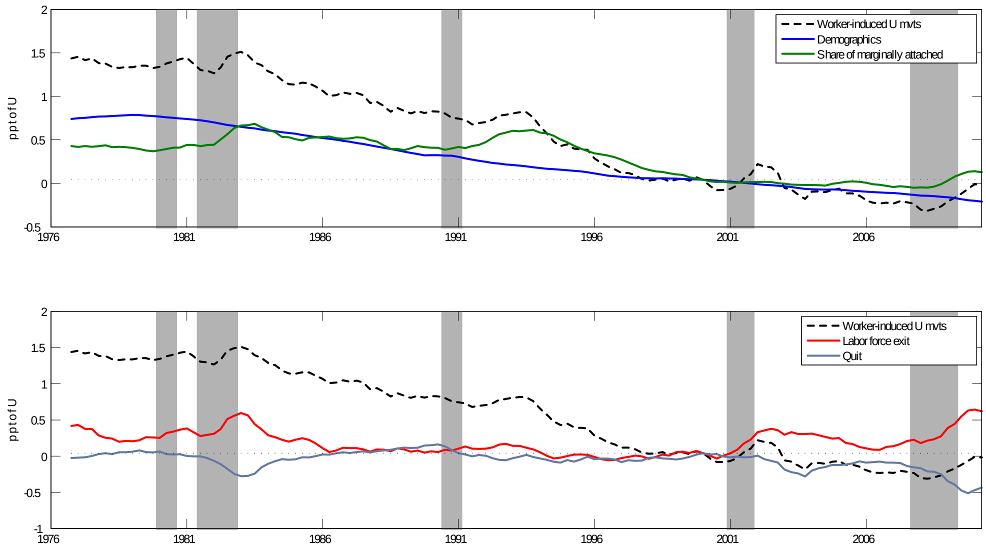

Figure 3: Decomposition of worker-induced unemployment movements into the contributions of quits, labor force participation propensity, labor force attachment and demographics, 1976-2010. The plotted series are 4-quarter moving averages.

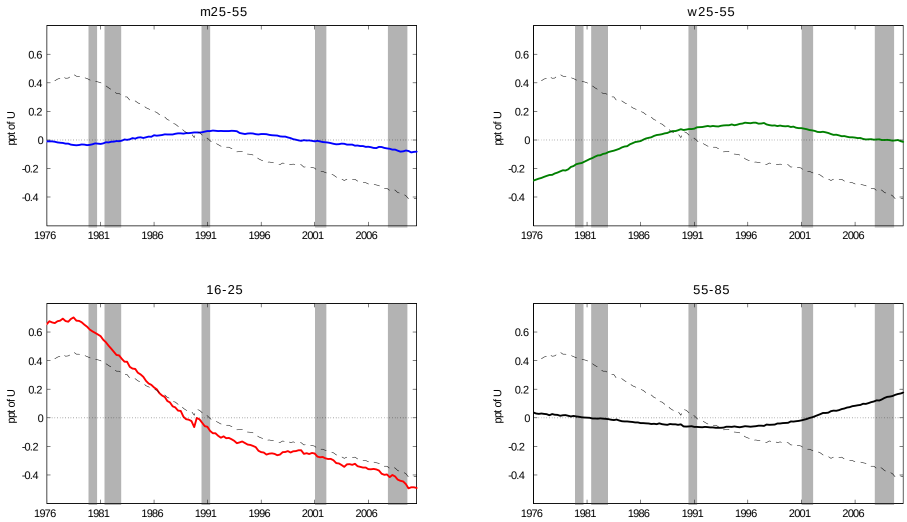

Figure 4: Decomposition of the effect of demographics on unemployment (du_{it}^{demog}) for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of demographics on unemployment, 1976-2010.

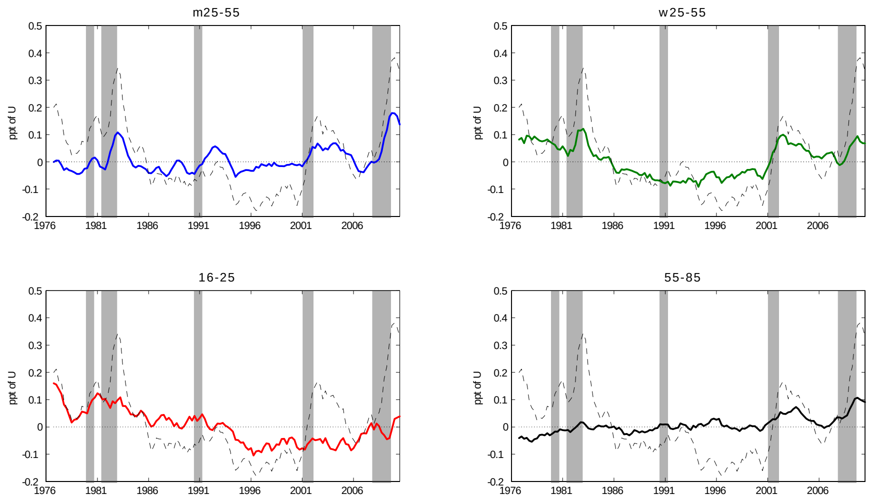

Figure 5: Decomposition of the effect of labor force attachment on unemployment (du_{it}^{LFI}) for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of demographics on unemployment, 1976-2010.

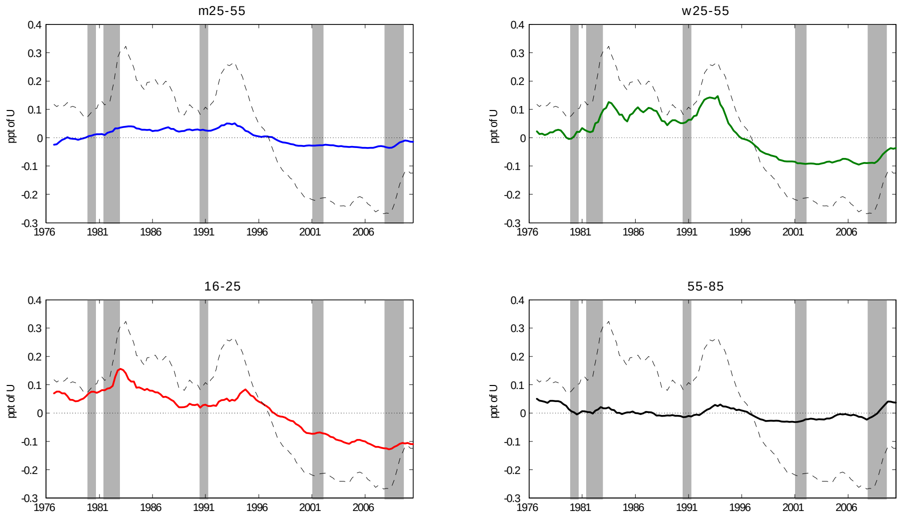

Figure 6: Decomposition of the effect of the composition of the inactivity pool on unemployment (du_{it}^{ILF}) for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of demographics on unemployment, 1976-2010.

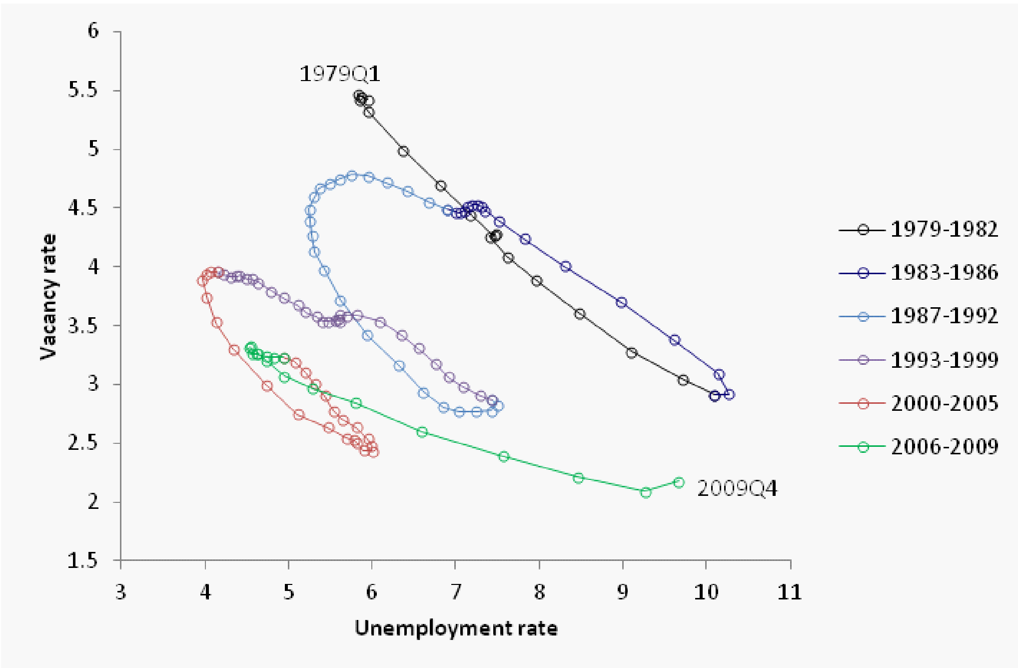

Figure 7: The US empirical U-V locus (the empirical Beveridge curve), 1979Q1-2009Q4. For clarity of exposition, we plot the 4-quarter moving averages of the unemployment and vacancy rates.

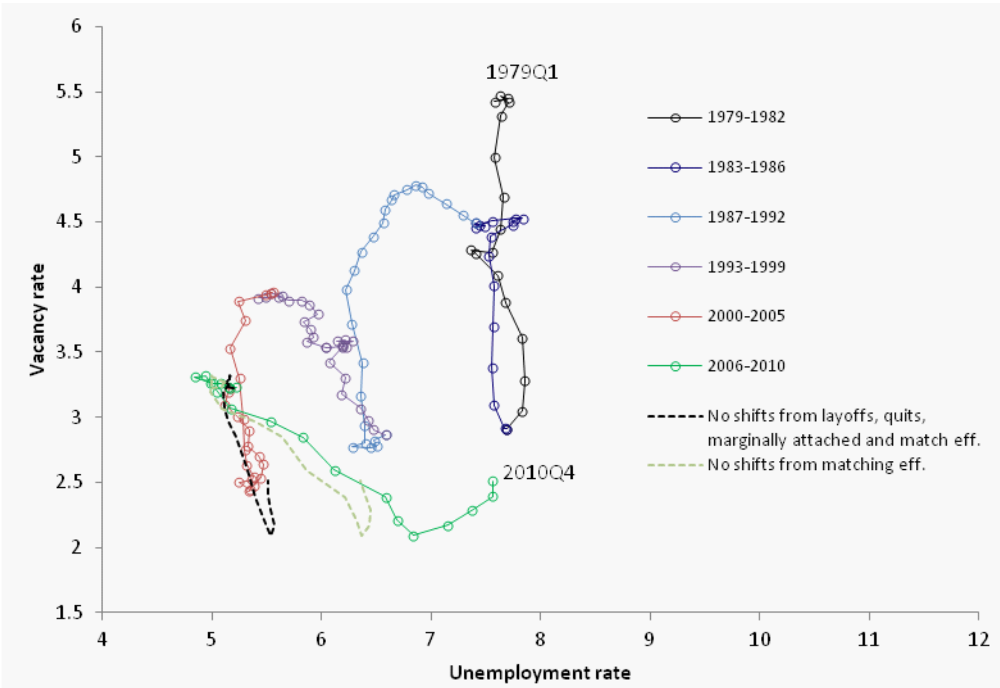

Figure 8: Shifts in the empirical Beveridge curve, 1979-2010. The dashed black line plots the Beveridge curve over 2006-2010 without shifts from layoffs, quits, changes in the share of marginally attached, and changes in matching efficiency. The dashed grey line plots the same Beveridge curve without shifts from layoffs, quits and changes in the share of marginally attached. 4-quarter moving averages of the unemployment and vacancy rates.

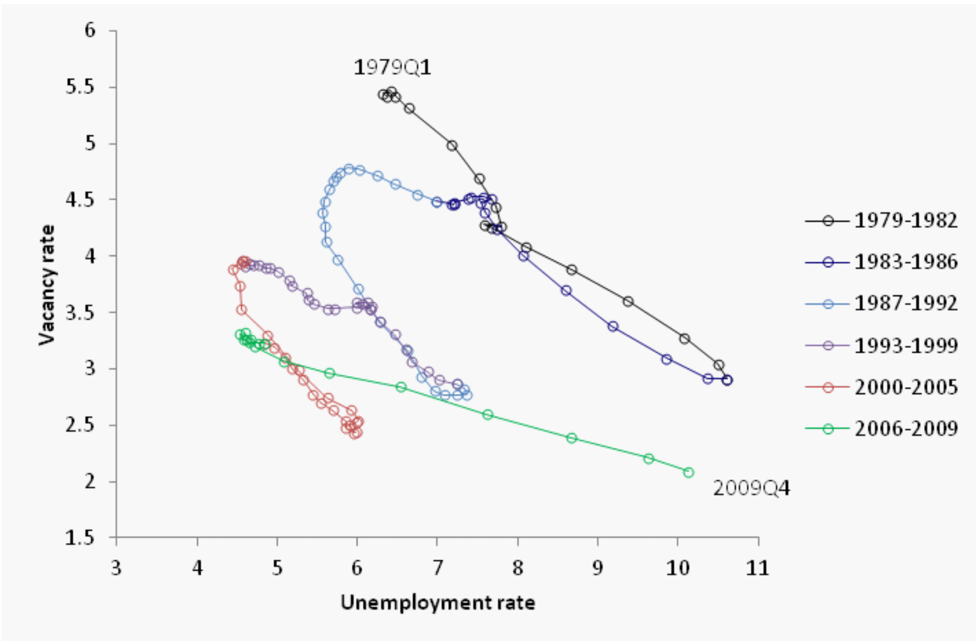

Figure 9: The theoretical Beveridge curve (the U^{ss}-V locus), 1979Q1-2009Q4. For clarity of exposition, we plot the 4-quarter moving averages of the unemployment and vacancy rates.

Table 1: Estimation

Dependent variable:	λ^{UE}	λ^{UE}	$\lambda^{IE\|LF}$
Sample (quarterly frequency)	1967-2009	1967-2009	1976-2009
Regression	(1)	(2)	(3)
Estimation	OLS	GMM	OLS
σ	0.62*** (0.01)	0.61*** (0.01)	--
$a_1(\lambda^{UE})$	--	--	0.23*** (0.0)
$a_2(I^U/I)$	--	--	-0.31*** (0.03)
R^2	0.85	--	0.85

Note: Standard-errors are reported in parentheses. In equation (2), we use 3 lags of v and u as instruments. All regressions include a constant. *** denotes significance at the 99% confidence interval

Table 2: Variance decomposition of steady-state unemployment, 1976:Q1-2009:Q4

		Raw data	Trend component	Cyclical component
Firm-induced U mvts:	*Hiring*	0.37	-0.01	0.52
	Layoffs	0.31	0.11	0.37
Worker-induced U mvts:	*Quits*	-0.06	-0.01	-0.07
	LF exit	0.12	0.23	0.10
	I^U/U { *LM entry* / *LM exit*	0.07	0.22 { 66% / 33%	0.05
	Demographics	0.06	0.41	0.00
	Other	0.03	0.04	0.03
Matching efficiency		0.10	--	--

Note: Trend component denotes the trend from an HP-filter (10^5) and cyclical component the deviation of the raw data from that trend. For the low-frequency decomposition ("trend component"), the contribution of I^U/I is further split into the percentage contribution of labor market entry (LM entry) from movements in λ^{IIU}, and labor market exits (LM exit) from movements in λ^{IIU} over 1994-2009.

Table 3: Variance decomposition of trend in unemployment *by* demographic group, 1976:Q1-2009:Q4

	Male 25-55	Female 25-55	Young 16-25	Old Above 55
Quits	0.25	0.21	**0.60**	-0.06
LF exit	0.16	**0.48**	**0.32**	0.03
I^U/I	0.12	0.37	**0.46**	0.04
Weight of group in labor force	0.38	0.30	0.18	0.14

Note: Each row sum to one. Numbers in bold indicate large contributions relative to the weight of the group in the labor force.

Table 4a: Variance decomposition of cyclical unemployment *by* demographic group, 1976:Q1-2009:Q4

	Male 25-55	Female 25-55	Young 16-25	Old Above 55
Layoffs	**0.52**	0.18	0.21	0.09
Quits	0.21	0.25	**0.50**	0.05
LF exit	0.35	0.25	**0.26**	0.14
I^U/I	0.14	**0.43**	**0.27**	0.16
Weight of group in labor force	0.38	0.30	0.18	0.14

Note: Each row sum to one. Numbers in bold indicate large contributions relative to the weight of the group in the labor force.

Table 4b: Variance decomposition of cyclical unemployment *of* demographic groups, 1976:Q1-2009:Q4

	$U^{\text{Male 25-55}}$	$U^{\text{Female 25-55}}$	$U^{\text{Young 16-25}}$	$U^{\text{Old 55+}}$
Hiring	0.44	0.50	0.69	0.32
Layoffs	**0.46**	0.32	**0.25**	0.38
Quits	**-0.03**	-0.07	**-0.10**	-0.02
LF exit	0.09	0.10	**0.06**	**0.18**
I^U/I	**0.02**	0.08	0.06	0.09
Other	0.02	0.06	0.04	0.04