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

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Abstract

This paper presents an accounting framework using CPS micro data and an aggregate matching function to analyze the determinants of unemployment movements at all frequencies. At business cycle frequencies, firms' hiring and layoff policies are the main determinants of unemployment fluctuations, consistent with standard business cycle models of the labor market (Mortensen and Pissarides, 1994). In contrast, at low frequencies, the downward trend in unemployment since the early 80s can be attributed to the aging of the baby boom and to a downward trend in inactive individuals' willingness to work, but not to trends in hiring and layoffs. Our results imply that the gradual leftward shift of the Beveridge curve over the last 30 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.

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1 Introduction

The unemployment rate in the US, or in any other OECD country, has displayed large fluctuations over the post war period, both at cyclical and low frequencies. Yet, despite decades of research, important questions about the determinants of unemployment fluctuations remain unanswered. First, at cyclical frequencies, most theories of unemployment (e.g., Mortensen and Pissarides (MP), 1994) focus on firms' labor demand, i.e., on firms' job creation and job separation conditions. Empirically, however, little is known about the importance of workers' labor supply decision, i.e., about the role played by individuals' willingness to work. Second, at low frequencies, a number of hypotheses have been advanced to explain the downward trend in US unemployment since the early 80s: the aging of the baby boom, lower labor force participation, lower union power, higher trend productivity growth, among others.[1] However, there is no consensus on the relative importance of these hypotheses. Finally, while it is common practice to treat separately cyclical and low frequency movements in unemployment, there is no good evidence that such a dichotomy is justified.[2]

To address these questions and study the economic mechanisms behind unemployment fluctuations, this paper presents an accounting framework using CPS matched micro data and an aggregate matching function to analyze the determinants of unemployment movements. Importantly, our framework covers all frequencies and does not a priori treat separately business cycle frequencies and low-frequencies.

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

Our accounting framework builds on a stock-flow model of unemployment in steady-state, as in Shimer (2007). Workers can transit between three labor market states: employment (E),

[1] Labor supply based explanations 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). Labor demand based explanations (i.e., mechanisms leading to higher labor demand) have also been suggested, such as declining union power and/or increasing wage flexibility (Davis, Faberman and Haltiwanger, 2006), rising trend productivity growth as in the late 1990s (Ball and Moffitt, 2001) or declining intensity of idiosyncratic labor demand shocks (Davis, Faberman, Haltiwanger, Jarmin and Miranda, 2010). See also Layard, Nickell and Jackman (2005).

[2] In fact, there are reasons to think it may not be. For instance, the hysteresis hypothesis (Blanchard and Summers, 1986) stipulates that previous unemployment can exert a persistent effect on subsequent unemployment.

unemployment (U) and inactivity (I) (i.e., out of the labor force), and the flows in and out of these three states determine the unemployment rate. We identify the economic decisions behind these flows from CPS matched micro data over 1976-2010 and from the existence of an aggregate matching function, and we decompose unemployment fluctuations into the contributions of five economic forces: hiring, layoffs, quits, labor market participation decisions, changes in matching efficiency –the ability of the labor market to match unemployed workers to jobs–, and demographics.

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 MP model to focus on job creation and job separation when studying unemployment fluctuations. Nonetheless, labor market participation decisions, in particular unemployed individuals' decision to exit the labor force and inactive individuals' willingness to work, exacerbate unemployment fluctuations: In recessions, unemployed workers are more likely to remain in the labor force, and inactive individuals have a stronger willingness to work 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.[3] Finally, while changes in matching efficiency 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, we find that the downward trend in unemployment since the early 80s (about -2 ppt) is driven by (i) demographics, specifically the aging of the baby boom generation, which lowered the unemployment rate by about 1ppt and (ii) a secular change in the composition of the inactivity pool, and more specifically, a downward trend in the fraction of marginally attached individuals since the mid 90s, which lowered unemployment by about $\frac{3}{4}$ percentage point.[4] Marginally attached individuals are individuals who want a job but are not looking for one and are part of the inactivity pool.[5] A lower fraction of marginally attached individuals in the inactivity pool lowers the unemployment rate, because the marginally attached have a higher propensity to join the unemployment pool than non-marginally attached inactives.[6]

[3] See Garibaldi and Wasmer (2005), Haefke and Reiter (2006), Campolmi and Gnocchi (2010), Christiano, Trabandt and Walentin (2010), Krussel, Mukoyama, Rogerson and Sahin (2011a, 2011b) for recent efforts to study the labor force participation decision.

[4] Another (smaller) factor is the increasing attachment of employed women to the labor force that lowered unemployment by about $\frac{1}{4}$ ppt through the early 90s.

[5] Non-marginally attached inactives are individuals who want do not want a job and are not looking for one.

[6] It is also true that marginally attached individuals also have a higher propensity (about 3 times larger) to

Since the role played by the composition of the inactivity pool is substantial, and as far as we know, previously undocumented, we explore this result further and show, using micro data on transitions in and out of marginal attachment, that the downward trend in the fraction of marginally attached individuals was caused by a decrease in people's willingness to work.[7] We conclude that a significant fraction of the downward trend in unemployment since the mid-90s is due to a change in the interest of inactive individuals in market work; a force that shrank the economy's labor supply (defined by including any individual who wants or has a job).

We find no evidence of a trend in the component of unemployment driven by firms' hiring and layoff policies. Our results thus suggest that labor demand explanations of unemployment's trend played a less direct role than typically assumed. According to a standard MP model, an explanation based on higher trend productivity growth and real wage rigidity (Ball and Moffitt, 2001) should have led to higher job creation and higher equilibrium labor market tightness and hence to a trend in the hiring component of unemployment. Similarly, explanations based on higher wage flexibility or on a declining intensity of idiosyncratic labor demand shocks (Davis et al., 2010) should imply a secular decline in the hazard rate of being laid off and becoming unemployed. However, we find that the layoff rate to unemployment has remained constant once one controls for demographic changes. Finally, our results have broader implications given Davis et al.'s (2010) finding that the downward trend in the unemployment inflow rate is linked to two secular trends: a 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.

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.[8] 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

find a job than non-marginally attached inactive individuals. However, the marginally attached's propensity to join unemployment is so much higher (about 10 times larger) than that of the non-marginally attached inactive individuals, that a higher fraction of marginally attached raises the unemployment rate.

[7] More specifically, by an increase in the propensity of the marginally attached to stop wanting a job (i..e, become non-marginally attached, i.e., "truly" inactive), and from a decrease in the propensity of the "truly" inactive to start wanting a job (i.e., become marginally attached).

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

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 a large 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.[9] 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,[10] 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 to interpret. Indeed, different economic forces can generate changes in unemployment inflows or outflows. For instance, finding a job and leaving the labor force are both unemployment outflows, but the economic forces behind these changes are quite different. Similarly, a layoff, a quit and an entry to the labor force are all unemployment inflows, but again the economic forces are probably distinct. Indeed, layoffs are countercyclical, while quits are procyclical. 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 and higher labor demand), or because more inactive individuals decided they wanted a job (i.e., higher labor supply). By addressing these shortcomings, our approach can provide additional information on the determinants of unemployment movements and this information can serve as a useful input into the development of models of the labor market and macroeconomic fluctuations. 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).[11]

[9] 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).

[10] 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.

[11] The debate recently gathered a lot of attention in policy and academic circles. See, for instance, Neumark's

The next section lays the theoretical groundwork for our decomposition. Section 3 presents the empirical work behind the estimation and interpretation of the hazard rates. Section 4 and 5 present the results of our decomposition, first aggregated and then disaggregated by demographic groups, Section 6 discusses the implications of our results, Section 7 revisits our unemployment decomposition in Beveridge curve space. Section 8 concludes.

2 An unemployment accounting framework

In this section, we present an accounting framework that isolates the main mechanisms behind unemployment movements. Specifically, we show how, by using CPS matched micro data to capture labor flows, we can decompose unemployment movements into meaningful economic concepts. We identify firm-induced unemployment movements –due to hiring and layoffs–, worker-induced unemployment movements –due to quits and labor market participation decisions– and the effect of demographics.

The next subsection presents the concept of steady-state unemployment (with three labor market states) that underlies our decomposition, and the reader familiar with this concept may wish to jump directly to subsection 2.2, where we present our interpretation of the flows, which is at the heart of our exercise.

2.1 A decomposition of steady-state unemployment

After controlling for demographic changes, this subsection presents the concept of steady-state unemployment; the starting point of our exercise.

2.1.1 Accounting for demographics

The aggregate unemployment rate reflects the labor market experience of demographics groups with different and time varying characteristics.[12] Changes in demographics could then affect the cyclical and low-frequency properties of unemployment, and we allow for heterogeneity across demographic groups.

(2011) survey on the effect and desirability of two policies (hiring credits and workers subsidies) to spur job creation.

[12] A number of researchers (e.g., Perry, 1970, Flaim, 1979, Shimer, 1998) have emphasized 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 rate 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).

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 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

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

2.1.2 Steady-state unemployment by demographic group

We now introduce the concept of 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 months. 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[13]

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

where s_{it} and f_{it} are

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

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

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

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

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 $1-\lambda_{it}^{IE|ILF}=\lambda_{it}^{IU}/\lambda_{it}^{ILF}$.

2.1.3 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 function of changes in the hazard rates[14]

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

so that the aggregate unemployment rate can be decomposed as

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

2.2 Interpreting the flows of unemployment

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 exit. In this section, we present our approach to interpret the different components λ_{it}^{AB}.

2.2.1 Interpreting movements in the job finding rate: hiring

We model the aggregate job finding rate $\lambda_t^{UE}\equiv\sum_{i=1}^{N}\omega_i\frac{u_i}{u}\lambda_{it}^{UE}$ with a matching function, a device commonly found in macroeconomic models with search and search and matching frictions (e.g., Pissarides, 2001). This allows us to interpret movements in job finding probability in terms of changes in hiring and changes in matching efficiency.

Specifically, the matching function relates the flow of new hires to the stocks of vacancies and unemployment. Using a standard Cobb-Douglas matching function with constant returns

[14] At this stage, we have not specified the order of our Taylor expansion. While our notation suggests a first-order expansion, 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.

to scale, 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.[15]

The job finding rate λ_t^{UE} is the ratio of new hires to the stock of unemployed, and 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.[16]

2.2.2 Interpreting movements in the job separation rate: layoffs and quits

Movements in the job separation rate λ_{it}^{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_{it}^{EU}, we will thus use micro data to refine our measure of separation and study instead separately $\lambda_{it}^{EU^l}$ and $\lambda_{it}^{EU^q}$ with $\lambda_{it}^{EU} = \lambda_{it}^{EU^l} + \lambda_{it}^{EU^q}$, with $\lambda_{it}^{EU^l}$ the hazard rate of moving from employment to unemployment through a layoff and $\lambda_i^{EU^q}$ the hazard rate of moving from employment to unemployment through a quit. We make this distinction for each demographic group i.

2.2.3 Interpreting movements in and out of the labor force

Considering (4), the last terms we need to interpret are λ_{it}^{EI}, λ_{it}^{UI}, and $\frac{\lambda_{it}^{IE}}{\lambda_{it}^{ILF}}$, which capture movements in-and-out of the labor force. Since the following discussion applies to any demographic group, to lighten notations, we omit the group i and time t indexes in this section.

[15] 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.

[16] In Barnichon and Figura (2011), we study the determinants of aggregate matching efficiency movements over 1976-2010.

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

Movements in λ^{EI} and λ^{UI} capture changes in the propensity of individuals (employed or unemployed) to leave the labor force. Thus, we will interpret movements in unemployment originating in λ^{UI} and λ^{EI} as driven by individuals' decisions to stay in or exit the labor force.[17]

Interpreting $\lambda^{IE|ILF}$: hiring and composition of the inactivity pool

Movements in $\frac{\lambda^{IE}}{\lambda^{ILF}}$ are a priori difficult to interpret since they not only depend on inactive individuals' propensity to join the labor force (a decision of the worker) but also on job availability (which depend on firms' hiring policy). In this subsection, we show how simple theoretical considerations lead us to decompose movements in $\lambda^{IE|ILF}$ into two easily interpretable components: (i) changes in the job finding rate of the unemployed (λ^{UE}) and (ii) changes in the fraction of marginally attached inactive individuals –individuals that are not searching for a job but nonetheless want one–[18] in the inactivity pool. In Section 3, we then verify empirically that this approach is valid, as these two components explain almost all of the variance of $\lambda^{IE|ILF}$.

For clarity of exposition, we only sketch the principle of our approach and leave a more detailed description of our argument in the Appendix. We present our approach in two steps:

First, we temporarily assume that the inactivity pool is homogenous (apart from demographic characteristics that we already control for). In that case, movements in $\lambda^{IE|ILF}$ should be captured by movements in λ^{UE} only. Our reasoning goes as follows. $\lambda^{IE|ILF}$ is the hazard rate of finding a job conditional on joining the labor force. In other words, it corresponds to inactives' job finding rate immediately upon entering the labor force, i.e., it is the job finding rate of individuals with an unemployment duration of zero. If we assume that there exists a relationship (stable over time) between the job finding rate of a labor force entrant with zero unemployment duration and the job finding rate of a labor force entrant who joined the labor force d periods ago, movements in $\lambda^{IE|ILF}$ should be captured by movements in the job finding

[17] This interpretation is uncontroversial for λ^{UI}. For λ^{EI}, one could imagine that some EI transitions are triggered by layoffs (decisions of the firm) that lead the individuals to leave the labor force, thereby complicating our interpretation of an EI transition as being only a decision of the worker. However, employed workers subject to a layoff are eligible for unemployment benefits (unlike workers who quit) and have therefore a strong interest in staying in the labor force (as unemployed). Thus, an EI transition is more likely to originate in a quit (a decision of the worker) than in a layoff (a decision of the firm). We thus choose to interpret EI transitions as capturing decisions of the worker. We will later see that this interpretation is consistent with our empirical results: At low frequencies, the EI margin explains only a small fraction of the trend in unemployment until the early 90s (-$\frac{1}{4}$ppt), but the effect is driven by one particular demographic group (prime-age females). Since firms are unlikely to have different layoff policy for males and females, this suggests that the EI trend was driven by prime-age females' decisions to stay in or exit the labor force, and not by firms employment policies. At cyclical frequencies, the EI margin of unemployment movements plays a marginal role.

[18] In contrast, an individual is considered unemployed if he does not have a job *and* is actively looking for one.

rate of unemployed labor force entrants. But since the job finding rate of labor force entrants comoves very closely with the average job finding rate λ^{UE} (Shimer 2007, and Elsby, Michaels and Solon 2009), movements in $\lambda^{IE|ILF}$ should be captured by movements in λ^{UE} and would therefore be easily interpretable as changes in hiring (and matching efficiency) following our previous discussion of λ^{UE}.

Second, we relax the assumption of an homogenous inactivity pool. In particular, it is well known (Jones and Riddell, 1999) that the pool of inactive individuals 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 (in terms of their job finding probability) from the "truly" inactive, –individuals who do not want a job and are indifferent to the state of the labor market. Because of such heterogeneity, changes in the fraction of marginally attached in the inactivity pool may generate movements in $\lambda^{IE|ILF}$ unexplained by movements in λ^{UE}. Thus, movements in $\lambda^{IE|ILF}$ can also depend on $\frac{I^U}{I}$, the fraction of marginally attached in the inactivity pool, with I^U the number of marginally attached individuals.

We can thus expect $\lambda^{IE|ILF}$ to be a function of λ^{UE} and $\frac{I^U}{I}$, which after log-linearizing, can be estimated by running the regression

$$\ln \lambda_t^{IE|ILF} = a_0 + a_{UE} \ln \lambda_t^{UE} + a_I \ln \frac{I_t^U}{I_t} + \varepsilon_t. \tag{8}$$

If our interpretation is correct and the regression R^2 is high, we can then decompose movements in $\frac{\lambda_t^{IE}}{\lambda_t^{ILF}}$ into: (i) changes in hiring (and matching efficiency) and (ii) changes in the fraction of inactive individuals who want a job. Of course, ultimately, the validity of our approach is an empirical question that we address (and answer positively) in Section 3.

2.3 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 and using (7) and (8), we can decompose unemployment movements into[19]

$$\begin{aligned} du_t &= du_t^{demog} + du_t^{hiring} + du_t^{layoff} + du_t^{quit} \\ &\quad + du_t^{LF\ exit} + du_t^{\frac{I^U}{I}} + du_t^{m_0} + \mu_t \end{aligned} \tag{9}$$

[19]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 2. The expressions for the first- and second-order coefficients are shown in the Appendix.

with du_t^x, $x \in \{demog,\ layoff,\ quit,\ LF\_I,\ I^U/I,\ m_0\}$, capturing the changes in unemployment due, respectively, to changes in demographics, hiring, layoffs, quits, labor force exits (originating in UI or EI transitions), the fraction of marginally attached ($\frac{I^U}{I}$) and matching efficiency. The expressions for the du_t^x term are shown in the Appendix. The error term μ_t captures mostly the movements in ε_t –the movements in $\lambda_t^{IE|ILF}$ not explained by λ_t^{UE} or $\frac{I_t^U}{I_t}$, as well as the 2^{nd}-order approximation error.

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

$$Var\,(y+z) = Cov(y, y+z) + Cov(z, y+z) \tag{10}$$

with $y, z \in \mathbb{R}$ 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.

3 Estimation

3.1 Measuring individuals' transition rates

To identify 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.[20] The estimated transition probabilities suffer from time-aggregation bias because 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 job finding rates, the extent of time-aggregation bias differs across different groups (e.g. job losers and job quitters). Not taking this into account could lead to erroneous corrections (e.g., the E-U^l and the E-U^q transitions). Extending Shimer (2007), we thus consider a 5-state 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, lf.[21] 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 $S = \left\{U^l, U^q, U^{lf}, E, I\right\}$. To correct for the time aggregation bias, we consider a continuous environment in which data are available at discrete dates t. Denote $N_t^{AB}(\tau)$ the number of workers who were in state A

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

[21] 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).

at $t \in \mathbb{N}$ and are in state B at $t+\tau$ with $\tau \in [0,1]$ and define $n_t^{AB}(\tau) = \frac{N_t^{AB}(\tau)}{\sum\limits_{X \in S} N_t^{AX}(\tau)}$ 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:[22]

$$\dot{n}_t^{AB}(\tau) = \sum_{C \neq B} n_t^{AC}(\tau)\lambda_t^{CB} - n_t^{AB}(\tau) \sum_{C \neq B} \lambda_t^{BC}, \qquad \forall\ A \neq B. \tag{11}$$

We then solve this system of differential equations to obtain the transition rates for each demographic group. We use data from the CPS from January 1976 through December 2010 and calculate the quarterly series for the transition rates over 1976Q1-2010Q4 by averaging the monthly series.

3.2 Estimating a matching function

We estimate a matching function by regressing

$$\ln \lambda_t^{UE} = (1-\sigma) \ln \theta_t + \ln m_0 + \zeta_t \tag{12}$$

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

$$\ln m_{0t} = \ln m_0 + \zeta_t. \tag{13}$$

We estimate (12) with monthly data using the composite help-wanted index presented in Barnichon (2010) as a proxy for vacancy posting.[23] We use non-detrended data over 1967:Q1-2010: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.

[22] 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..)

[23] 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.

3.3 Estimating the labor force entry rate of inactive individuals

To interpret $\lambda^{IE|ILF}$ in terms of hiring and composition of the inactivity pool, we proceed as described in Section 2 and estimate

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

To obtain a measure of $\frac{I_t^U}{I_t}$ over 1976:Q1-2010: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?".[24] Column (3) of Table 1 presents the results of the regressions estimated over 1976-2010. 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 $\lambda^{IE|ILF}$.[25]

Note that a_I 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.

3.4 Interpreting $\frac{I^U}{I}$: willingness to work

Previewing our decomposition results, we will find that the fraction of marginally attached individuals $\frac{I^U}{I}$ plays an important and, as far as we know, undocumented, role. However, since many forces can lead to movements in $\frac{I^U}{I}$, interpreting $\frac{I^U}{I}$ is a priori difficult.[26]

To do so, we use the fact that the redesign of the CPS in 1994 allows us to measure flows in and out of I^U over 1994-2010.[27] Specifically, we decompose the stock $\frac{I^U}{I}$ into the contributions

[24] Importantly, the phrasing of the question did not change over 1976-2010, allowing us to estimate a time-series of $\frac{I_t^U}{I_t}$ over the whole sample.

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

[26] For instance, movements in $\frac{I^U}{I}$ could arise out of a composition effect (for instance, if unemployed have the highest propensity to become marginally attached, an increase in unemployment will mechanically raise $\frac{I^U}{I}$) or out of changes in the propensity of the marginally attached to want/not want a job.

[27] After 1994, the question "Do you currently want a job now, either full or part-time?", that allows us to

of its flows by splitting the labor market state "inactivity" into two states: truly inactive (I^I) and marginally attached (I^U). We then have four states: E, U, I^U and I^I, and we can measure the flows in between these four states over 1994-2010.

We can then express $\frac{I^U}{I}$ as a functions of 12 hazard rates, and log-linearizing, we can write

$$d\ln\frac{I_t^U}{I_t} = \sum_{A\neq B}\gamma^{AB} d\ln\lambda_t^{AB} + \kappa_t \tag{14}$$

with $\left\{\gamma^{AB}\right\}$ the coefficients of the log-linearization.

While decomposition (14) can appear cumbersome and difficult to interpret, 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 movements in the fraction $\frac{I_t^U}{I_t}$ have a simple interpretation. The two hazard rates $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$ capture the propensity of inactive individuals to want, or not want, a job, so that movements in $\frac{I^U}{I}$ can be seen as changes in inactive individuals' willingness to work, i.e., movements in their labor supply.

Specifically, we find that

$$d\ln\frac{I_t^U}{I_t} \simeq \gamma^{I^U I^I} d\ln\lambda_t^{I^U I^I} + \gamma^{I^I I^U} d\ln\lambda_t^{I^I I^U}. \tag{15}$$

Figure 1 plots aggregate movements in I^U/I over 1994-2010 along with the movements in I^U/I generated solely by movements in $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$ according to equation (15) and shows that these two hazard rates account for virtually all of the movements in $\frac{I_t^U}{I_t}$ since 1994. A variance decomposition exercise confirms it and shows that $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$ account for, respectively, 66% and 33% of the variance of $\frac{I_t^U}{I_t}$ (Table 2).

4 An empirical decomposition of unemployment fluctuations

4.1 The main components of unemployment fluctuations

In this section, we use (9) to decompose unemployment rate fluctuations into the contributions of six components: hiring, layoff, quit, labor force exit, fraction of marginally attached in the inactivity pool 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 2 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

measure the fraction of marginally attached, was asked to all rotation groups. Before 1994, the question was only asked to the *outgoing* rotation groups and thus did not allow measurement of the flows in and out of I^U.

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 (9) confirms this impression, and Table 2 shows that 90% of the trend in unemployment since 1976 is the result of changes in demographics, labor market participation decisions and quits.[28] In contrast, about 90% of unemployment cyclical fluctuations are the result of hiring and layoff (excluding movements due to changes in matching efficiency).

Studying the components of unemployment in more detail confirms this conclusion. Figure 3 presents the contributions of hiring, layoff and matching efficiency, and Figure 4 presents the contributions of quit, composition of the inactivity pool ($\frac{I^U}{I}$) as well as demographics. It is apparent that the firm' driven components display little evidence of a trend, while the worker' driven components display little cyclical fluctuation.

Thus, our results support the trend-cycle dichotomy for US unemployment, as the factors behind the trend in the worker-driven component of unemployment did not affect firms' hiring and layoff policies. Thus from now on, we will discuss low frequencies and business cycle frequencies separately.

4.2 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 declining union power and/or increasing wage flexibility (Davis, Faberman and Haltiwanger, 2006), rising trend productivity growth as in the late 1990s (Ball and Moffitt, 2001) or declining intensity of idiosyncratic labor demand shocks (Davis, Faberman, Haltiwanger, Jarmin and Miranda, 2010). 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 explanation and also suggests another explanation based on secular changes in the composition of the inactivity pool.

Figure 4 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

[28] 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 (9) to each frequency range.

pool ($du_t^{\frac{I^U}{I}}$), and changes in labor force attachment of employed workers in the first half of the sample ($du_t^{LF\ exit}$). Together, these three factors lowered unemployment by about 2 ppt since the early 80s.

Table 2 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 1 percentage point over 1980-2010, changes in labor force attachment lowered the unemployment rate by about $\frac{1}{4}$ percentage point until the early 90s, and a downward trend in the fraction of marginally-attached individuals lowered the unemployment rate by a substantial, yet, as far as we know, hitherto unnoticed, $\frac{3}{4}$ percentage point after the mid-90s.

Since the latter contribution is substantial, and as far as we know, previously undocumented, we explore the contribution of $\frac{I^U}{I}$ further. Using our interpretation of $\frac{I^U}{I}$ from Section 3.4, we know the trend in $\frac{I^U}{I}$ is due solely 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 $\lambda^{I^U I^I}$).[29] 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. We conclude that a significant fraction of the downward trend in unemployment since the mid-90s is due to a change in the interest of inactive individuals in market work.

After controlling for demographic changes, the component of unemployment driven by hiring and layoffs shows little evidence of a trend (Figure 3), and Table 2 confirms that hiring and layoffs only account for a small fraction of low-frequency unemployment movements.[30]

[29] While the variance decomposition based on (14) is reported in Table 2 for unfiltered data, the variance decomposition is similar at low and cyclical frequencies.

[30] The absence of a trend in the unemployment inflow rate for job losers does not in contradict 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 (Figure 3). 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.

4.3 Business cycle frequencies

Turning to business cycle frequencies, Table 2 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.

Overall, the cyclical contribution of the worker-driven component is small compared to that of hiring and layoff. However, labor force attachment and the share of marginally attached individuals do exhibit cyclical fluctuations. As shown in Figure 4, in recessions, unemployed 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 unemployment fluctuations, as workers are less likely to quit in recession.[31]

With an average contribution of 10 percent, changes in matching efficiency have, a non-trivial impact on the equilibrium unemployment rate. Moreover, Figure 3 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.

5 Heterogeneity and demographics

To better understand the movements in the components of unemployment, 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.

At low frequencies, we find that the contribution of demographics owes primarily to the aging of the population. Moreover, women are behind the decrease in labor force attachment that lowered unemployment through the mid 1990s. Since the mid 1990s, the young are responsible for a large fraction of the contribution of lower labor supply (through lower willingness to work) to the trend in unemployment.

At business cycle frequencies, we find that all demographic groups display countercyclical labor force attachment when unemployed. However, the different margins of unemployment fluctuations play different roles across demographic groups, in line with the common view that different demographic groups have different labor supply elasticities. In particular, firm-related transitions, i.e., hiring and layoffs, are more important in explaining cyclical movements

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

in unemployment for prime age males, while labor market participation decisions are relatively more important for the young, the old, and prime age females.

We now present these results in more details.

5.1 Low frequencies

We first study low-frequencies. Figure 5 decomposes the movements in du_t^{demog} plotted in Figure 4 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.

To explore the factors behind the trends in labor force attachment, $du_t^{LF\ exit}$, and the fraction of marginally attached individuals, $du_t^{\frac{I^U}{I}}$, Figures 6 to 8 decompose the movements in $du_t^{LF\ exit}$ and $du_t^{\frac{I^U}{I}}$ plotted in Figure 4 into the contributions of the same four demographic groups, and Table 3 provides variance decompositions of the contribution of each demographic group to movements in $du_t^{LF\ exit}$ and $du_t^{\frac{I^U}{I}}$.

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 of employed prime-age females, supporting Abraham and Shimer's (2001) hypothesis. Employed prime-age females had a declining tendency to leave their job and the labor force until the early 90s, which lowered the unemployment rate, while the reverse was true for prime-age male (Figure 6 and Table 3).[32]

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 started earlier) for young individuals. Moreover, the *effect* of these trends on unemployment is especially strong amongst young workers because of their high average unemployment. As a result, while young workers represent only 18% of the labor force, they account for 46% of the downward trend in unemployment coming from composition of the inactivity pool (Table 3). In contrast, because of their low average unemployment, the contribution of prime-age males is relatively

[32] A stronger labor force attachment of employed individuals lowers the unemployment rate, because employed individuals are much less likely to enter the unemployment pool than inactive individuals.

small compared to their labor force share.[33]

5.2 Business cycle frequencies

We apply our accounting decomposition (9) to the unemployment rate of each demographic group, and Table 4 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 workers (Figure 9). In contrast, the picture is reversed for layoffs, which play little role for young workers and are very important for prime age males. Table 4 confirms this result, and shows that layoffs explain 46% of the variance of prime-age males unemployment, but only 25% of young workers unemployment

Both labor force attachment and the fraction of marginally attached tend to be countercyclical for all groups (Figure 7 and 8). Yet, as shown in Table 4, these two aspects of labor market participation play a much bigger role for the unemployment rate of the young, the old and prime-age females. For instance, the labor force exit decision of unemployed individuals is important in understanding the unemployment rate of older workers with a contribution of 21% (and is probably linked to their retirement decision), but plays a much smaller role for prime age males with a contribution of 10%. In a similar vein, movements in the fraction of inactive individuals who want a job plays a marginal role for prime-age individuals (with a contribution of 2%), but is much more important for old individuals or prime-age females (with contributions of respectively 9% and 8%). These findings are consistent with the common view that these demographic groups exhibit a more elastic labor supply than prime-age males.[34]

6 Theoretical implications

Low-frequency movements: At low-frequencies, we found no evidence of a trend in the component of unemployment driven by firms' hiring and layoff policies. Thus, our results suggest that labor demand explanations of unemployment's trend, played a less direct role than typically assumed. An explanation based on rising trend productivity growth and real wage

[33] 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.

[34] As prime-age males are the main income earners in many households, they display a relatively inelastic labor supply. Labor market participation could be a lot more "elastic" (in the sense of more responsive to changes in household income and wealth) 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).

rigidity (Ball and Moffitt, 2001) would imply, according to a standard MP model, rising job creation and rising equilibrium labor market tightness and hence a trend in the hiring component of unemployment. Explanations based on lower union power and/or higher wage flexibility, or on a lower variance of idiosyncratic shocks hitting firms, must justify the absence of any significant trend in the layoff rate to unemployment. For instance, 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.[35]

Our results imply that the unemployment inflow rate $s_t = \lambda_t^{EU} + \lambda_t^{EI}(1 - \lambda_t^{IE|ILF})$ (plotted in Figure A3 in the online Appendix) is caused by secular changes in demographics and inactives' willingness to work. This has a number of implications. 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. 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 the 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 demographics and 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.

Business cycle fluctuations: In the MP 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 countercyclical labor force attachment of the unemployed 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

[35] 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 suggests that the layoff rate also displays little trend over 1976-2010.

want a job, *look* for one or *stay* inactive.[36] These two mechanisms exacerbate unemployment fluctuations, and two important questions are why the unemployed are more likely to stay in the labor force during recessions (perhaps because of the extension of unemployment benefits during recessions), and why inactive individuals have a stronger willingness to work in recessions (perhaps because of wealth or added-worker effects).

Moreover, these labor market participation decisions play a bigger role for prime-age females and young individuals than for prime-age males, 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.

While quits and layoffs are indistinguishable in the MP model, since a match terminates when it is jointly optimal for both parties to separate, we found that the relative importance of quits and layoffs differs dramatically across demographic groups. This result shows that understanding theoretically the quit-layoff distinction is an important 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 3) is an interesting question for future research (Justiniano and Michelacci 2010, Barnichon and Figura 2011, Furlanetto and Groshenny 2011).

7 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 work 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 1976-2010 (Figure

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

10) in light of our findings. We examine two questions that have received a lot of attention in the literature and in the policy debate (Valletta 2005, Tasci and Lindner, 2010): (i) Why did the U-V locus progressively shift to the left since 1976?, and (ii) why did the Beveridge curve shift to the right so strongly in the 2008-2009 recession?

7.1 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 (9) 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_t denotes shifts of the Beveridge curve.

Our decomposition (9) implies a Beveridge curve since, by definition, $du_t^{hiring} = du_t^{hiring}(\theta_t)$, so that we have

$$\begin{aligned} du_t &= du_t^{demog} + du_t^{hiring}(\theta_t) + du_t^{layoff} + du_t^{quit} \\ &\quad + du_t^{LF\ exit} + du_t^{\frac{I^U}{I}} + du_t^{m_0} + \mu_t \end{aligned} \tag{16}$$

Unemployment moves along the Beveridge curve as firms adjust vacancies. Indeed, in the Pissarides (1985) model, the job creation condition $JC(\theta_t)$ determines the position of the unemployment rate on the Beveridge curve (16) 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 (16) 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...[37] In a more general model with endogenous separation or endogenous labor force participation however, these Beveridge curve "shifters" typically comove with labor market tightness θ_t. 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 the "shifters" will shift the empirical Beveridge only if they are "unusual" given the movements in θ_t.[38]

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

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

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

$$du_t^x = \alpha_x + \beta_x d \ln \theta_t + \varepsilon_t^x$$

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

7.2 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 $\varepsilon_t = \sum_x \varepsilon_t^x$ since the early 80s (Figure 11). Figure 12 plots the total shifts ε_t along with the shifts generated solely by layoffs (ε_t^{layoff}) as well as the shifts generated solely by matching efficiency ($\varepsilon_t^{m_{0t}}$). The secular leftward shift of the Beveridge curve is clearly apparent but cannot be explained by shifts due to layoffs. Given the absence of a trend in matching efficiency movements, the secular shift in the empirical Beveridge curve over the last 35 years is driven by changes in demographics and labor market participation decisions. A variance decomposition exercise based on $\varepsilon_t = \sum_x \varepsilon_t^x$, confirms this conjecture. Shifts due to layoffs explain 13% of the total shifts in the Beveridge curve, while demographics account for 37%, composition of the inactivity pool 32% and labor force attachment 14%.

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

Proceeding in a similar fashion, one can decomposes the dramatic shift over 2006-2010 (green solid line in Figure 11) into its subcomponents. As can be seen in Figure 12, exceptionally low matching efficiency explains about a half of the shift in the Beveridge curve, and unusually large layoffs account for about another third of the shift. 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, 2011 for an exploration of the sources of that decline).

8 Conclusion

This paper presents an accounting framework to decompose unemployment fluctuations at all frequencies into the contributions of demographics and hiring, layoffs, quits, 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 early 80s can be attributed to the aging of the baby boom and to a downward trend in inactive individuals' willingness to work but not to trends in hiring and layoffs. However, these aggregate results mask important differences across demographic groups, with labor force participation decisions playing a more important role for young individuals, old individuals and prime-age females at any frequency.

Two important sets of questions raised by our results are: (i) why are the unemployed more likely to stay in the labor force during recessions, and why does individuals' willingness to work increase during recessions, and (ii) what caused the downward trend in willingness to work since the mid 90s, especially amongst the young population.

We conclude our paper by showing that the gradual leftward shift of the empirical Beveridge curve over the last 30 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.

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, all characterized by different labor market institutions, experienced different secular trends in their unemployment rate and unemployment flows (Rogerson and Shimer, 2010).

Appendix

A second-order decomposition

Recall that

$$u_t^{ss} = \frac{s_t}{s_t + f_t} \tag{17}$$

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 (17) 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:

$$\begin{aligned}
\beta^{UE} &= -\frac{\lambda^{El} + \lambda^{Eq} + \lambda^{EI}\lambda^{IE|ILF})}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} + \lambda^{EI}\lambda^{IE|ILF})^2} \\
\beta^{EU} &= \frac{\lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI}}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} + \lambda^{EI}\lambda^{IE|ILF})^2} \\
\beta^{EI} &= -\frac{\lambda^{IE|ILF}(\lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} - \lambda^{EI}\lambda^{IU|ILF})^2} \\
\beta^{UI} &= -\frac{-\lambda^{IU|ILF}(\lambda^{El} + \lambda^{Eq} + \lambda^{EI}\lambda^{IE|ILF})}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} + \lambda^{EI}\lambda^{IE|ILF})^2} \\
\beta^{IE|ILF} &= -\frac{-\lambda^{UI}(\lambda^{El} + \lambda^{Eq}) + \lambda^{EI}(\lambda^{UE} + \lambda^{UI}))}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} - \lambda^{EI}\lambda^{IU|ILF})^2}
\end{aligned}$$

with $\lambda^{IU|ILF} = 1 - \lambda^{IE|ILF}$, the second-order terms

$$\begin{aligned}
\beta_2^{UE} &= \frac{2\lambda^{El} + \lambda^{Eq} + \lambda^{EI}\lambda^{IE|ILF})}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} + \lambda^{EI}\lambda^{IE|ILF})^3} \\
\beta_2^{EU} &= -\frac{2(\lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} - \lambda^{EI}\lambda^{IU|ILF})^3} \\
\beta_2^{EI} &= -\frac{2(\lambda^{IE|ILF})^2(\lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} - \lambda^{EI}\lambda^{IU|ILF})^3} \\
\beta_2^{UI} &= \frac{2(\lambda^{IU|ILF})^2(\lambda^{El} + \lambda^{Eq} + \lambda^{EI}\lambda^{IE|ILF})}{(\lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} + \lambda^{EI}\lambda^{IE|ILF})^3} \\
\beta_2^{IE|ILF} &= -\frac{-2(\lambda^{EI} - \lambda^{UI})(\lambda^{EI}\lambda^{UE} + \lambda^{EI}\lambda^{UI} + \lambda^{El}\lambda^{UI} + \lambda^{Eq}\lambda^{UI})}{(\lambda^{EI} + \lambda^{El} + \lambda^{Eq} + \lambda^{UE} + \lambda^{IU|ILF}\lambda^{UI} - \lambda^{EI}\lambda^{IU|ILF})^3}
\end{aligned}$$

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

$$du_t^{ss} = \sum_{A \neq B} \beta^{AB}(\lambda_t^{AB} - \overline{\lambda^{AB}}) + \sum_{A \neq B} \frac{\beta_2^{AB}}{2}(\lambda_t^{AB} - \overline{\lambda^{AB}})^2 + \textit{cross-order terms} + \eta_t \tag{18}$$

with $AB \in \{UE, EU, UI, EI, IE|ILF\}$.

Expression (18) is valid for any demographic group i. Combining (18) applied to group i with the fact that $du_t \simeq du_t^{ss}$ and

$$du_t = \sum_{i=1}^{N} (u_i d\omega_{it} + \omega_i du_{it}),$$

we can decompose unemployment according to

$$du_t = \sum_{i=1}^{N} u_i d\omega_{it} + \sum_{A \neq B} \sum_{i=1}^{N} \omega_i \left(\beta_i^{AB} d\lambda_{it}^{AB} + \frac{\beta_{i,2}^{AB}}{2}(d\lambda_{it}^{AB})^2 \right) + \mu_t. \tag{19}$$

and write

$$\begin{aligned} du_t &= du_t^{demog} + du_t^{hiring} + du_t^{layoff} + du_t^{quit} \\ &\quad + du_t^{LF\ exit} + du_t^{\frac{I^U}{I}} + du_t^{m_0} + \mu_t \end{aligned}$$

with $du_t^{demog} = \sum_{i=1}^{N} u_i d\omega_{it}$,

$du_t^{hiring} = (1 + a_{UE})(1 - \sigma) \left(\beta^{UE} \frac{d\theta_t}{\theta_t} - \frac{\beta_2^{EU}}{2} \frac{(d\theta_t)^2}{\theta_t^2} \right) + \textit{cross-order terms}$ using (8) and (20),

$du_t^{layoff} = \beta^{EU}(\lambda_t^{EU^l} - \overline{\lambda^{EU^l}}) + \frac{\beta_2^{EU}}{2}(\lambda\lambda_t^{EU^l} - \overline{\lambda^{EU^l}})^2 + \textit{cross-order terms}$,

$du_t^{quits} = \beta^{EU}(\lambda_t^{EU^q} - \overline{\lambda^{EU^q}}) + \frac{\beta_2^{EU}}{2}(\lambda_t^{EU^q} - \overline{\lambda^{EU^q}})^2 + \textit{cross-order terms}$,

$du_t^{LF\ exit} = \beta^{EI}(\lambda_t^{EI} - \overline{\lambda^{EI}}) + \frac{\beta_2^{EI}}{2}(\lambda_t^{EI} - \overline{\lambda^{EI}})^2 + \beta^{UI}(\lambda_t^{UI} - \overline{\lambda^{UI}}) + \frac{\beta_2^{UI}}{2}(\lambda_t^{UI} - \overline{\lambda^{UI}})^2 +$ *cross-order terms*,

$du_t^{\frac{I^U}{I}} = a_I \left(\beta^{IE|ILF}(\lambda_t^{IE|ILF} - \overline{\lambda^{IE|ILF}}) + \frac{\beta_2^{IE|ILF}}{2}(\lambda_t^{IE|ILF} - \overline{\lambda^{IE|ILF}})^2 \right) + \textit{cross-order terms}$,

$du_t^{m_0} = (1 + a_{UE}) \left(\beta^{UE} \frac{dm_{0t}}{m_0} - \frac{\beta_2^{EU}}{2} \frac{(dm_{0t})^2}{m_0^2} \right) + \textit{cross-order terms.}$[39]

Note that, in order to model movements in job finding rate with a matching function, we use the approximation $d\lambda_{it}^{UE} \simeq d\lambda_t^{UE}$ because the job finding rates of different demographic

[39] Again, the cross-order term are omitted for clarity of exposition but available upon request.

groups are highly correlated.[40] As a result, we can write

$$\sum_{i=1}^{N} \omega_i \beta_i^{UE} d\lambda_{it}^{UE} = \beta^{UE} d\lambda_t^{UE} + \eta_t$$
$$= \beta^{UE} \lambda^{UE} \frac{dm_{0t}}{m_0} + \beta^{UE} \lambda^{UE} (1-\sigma) \frac{d\theta_t}{\theta} + \eta_t \quad (20)$$

with $\beta^{UE} = \sum_{i=1}^{N} \omega_i \beta_i^{UE}$ and $\eta_t = \sum_{i=1}^{N} \omega_i \beta_i^{UE} \left(d\lambda_{it}^{UE} - d\lambda_t^{UE} \right) \ll 1$, and similarly for the second-order terms, and substitute (20) into (19) to obtain our expression for du_t^{hiring}.

Interpreting $\lambda^{IE|ILF}$: hiring and composition of the inactivity pool

In this section, we show how simple theoertical considerations suggest that movements in $\lambda^{IE|ILF}$ can be decomposed into: (i) movements in λ^{IU} and (ii) changes in the fraction of marginally attached individuals.

Since $\lambda_t^{IE|ILF} = \frac{\lambda_t^{IE}}{\lambda_t^{ILF}}$ is a ratio of hazard rates and not probabilities, the definition of conditional probability does not strictly apply $\lambda_t^{IE|ILF}$. Thus, to proceed rigorously with our argument, we temporarily reason with probabilities, rather than hazard rates, and consider $P_t(IE|ILF)$, the fraction of inactive individuals who enter the labor force directly through employment over $[t, t+1[$.

First, assume that the inactivity pool is homogenous (apart from demographic characteristics that we already control for). In that case, movements in $P_t(IE|ILF)$ should be captured by movements in $P_t(UE)$ only, the probability that an unemployed finds a job over $[t, t+1[$. Our reasoning goes as follows. $P_t(IE|ILF)$ is the probability of finding a job conditional on joining the labor force. In other words, it corresponds to inactives' job finding probability immediately upon entering the labor force, i.e., it is the job finding probability of individuals with an unemployment duration of zero. If we assume that there exists a relationship (stable over time) between the job finding probability of a labor force entrant with zero unemployment duration and the job finding probability of a labor force entrant who joined the labor force d periods ago, movements in $P_t(IE|ILF)$ should be captured by movements in the job finding probability of unemployed labor force entrants. But since the job finding probability of labor force entrants comoves very closely with the average job finding probability $P_t(UE)$ (Shimer 2007, and Elsby, Michaels and Solon 2009), movements in $P_t(IE|ILF)$ should be captured by

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

movements in $P_t(UE)$ so that we can expect that

$$P_t(IE|ILF) = h(P_t(UE)) \tag{21}$$

with $h(.)$ a function independent of time.

Second, we relax the assumption of an homogenous inactivity pool. Time-varying differences in the composition of the inactivity pool and the composition of the unemployment pool can lead to time-varying differences between $P_t(IE|ILF)$ and $P_t(UE)$. In particular, 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 (in terms of their job finding probability) from the "truly" inactive, –individuals who do not want a job and are indifferent to the state of the labor market. Because of such heterogeneity, changes in the fraction of marginally attached in the NLF pool will generate movements in $P_t(IE|ILF)$ unexplained by movements in $P_t(UE)$.

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

$$P_t(IE|ILF) = \frac{I_t^U}{I_t} P_t(I^U E|I^U LF) + \left(1 - \frac{I_t^U}{I_t}\right) P_t(I^I E|I^I LF). \tag{22}$$

If the presence of marginally attached individuals is the only important source of heterogeneity mattering for movements in $P_t(IE|ILF)$, we can then assume that the conditional job finding probabilities of, respectively, marginally attached and truly inactive individuals can be expressed as functions of $P_t(UE)$ only, i.e.,

$$\begin{aligned} P_t(I^U E|I^U LF) &= f(P_t(UE)) \\ P_t(I^I E|I^I LF) &= g(P_t(UE)) \end{aligned}$$

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

Combining (21) and (22), we get

$$P_t(IE|ILF) = \frac{I_t^U}{I_t} f(P_t(UE)) + \left(1 - \frac{I_t^U}{I_t}\right) g(P_t(UE)). \tag{23}$$

To express (23) in terms of hazard rates, note that the period probability of transiting from A to B satisfies $P_t(AB) = 1 - e^{-\lambda_t^{AB}} \simeq \lambda_t^{AB}$ for λ_t^{AB} small. Since this is the case for $P_t(IE)$ and $P_t(ILF)$ with both λ_t^{IE} and λ_t^{ILF} small ($< .1$), we can write $P_t(IE) \simeq \lambda_t^{IE}$ and

$P_t(ILF) \simeq \lambda_t^{ILF}$ and write

$$\lambda_t^{IE|ILF} = \frac{\lambda_t^{IE}}{\lambda_t^{ILF}} \simeq \frac{I_t^U}{I_t} f(\lambda_t^{UE}) + \left(1 - \frac{I_t^U}{I_t}\right) g(\lambda_t^{UE}). \tag{24}$$

Log-linearize (24), we obtain the expression reported in the main text

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

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 1994m1-2010m12. That way, we capture the long-run trend in the transition probability. Over 1994m2-2010m12, 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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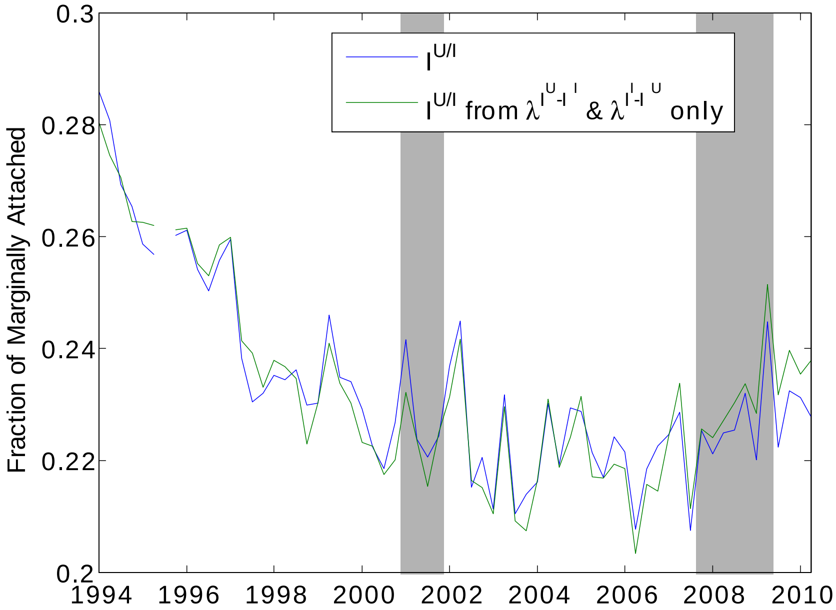


Figure 1: The fraction of marginally attached in the pool of inactives, I^U/I, along with the movements in I^U/I generated solely by movements in $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$. 1994-2010

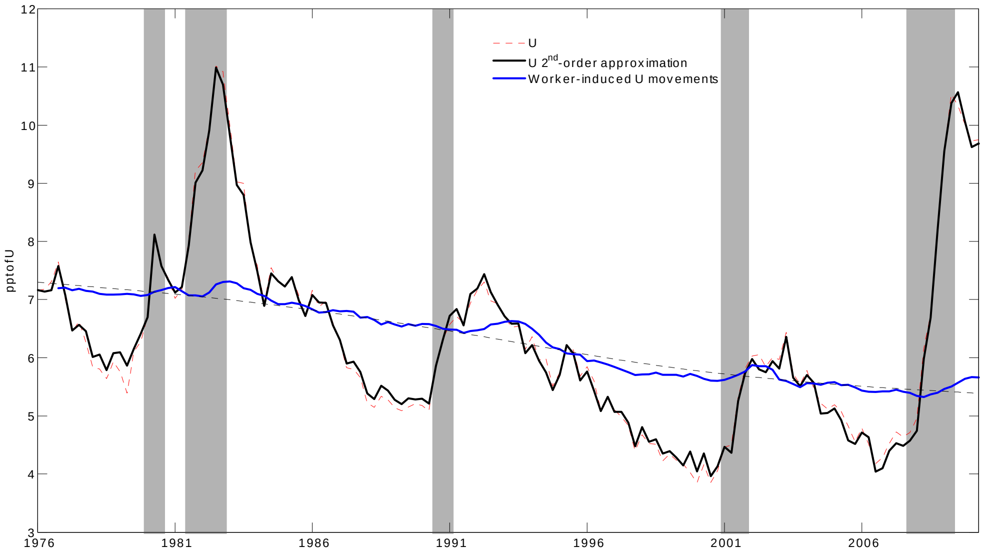


Figure 2: Steady-state unemployment (dashed red line), approximated unemployment from 2^{nd}order Taylor expansion (black line), and unemployment movements explained by demographics, labor force exit, composition of the inactivity pool and quits (blue line, labelled "worker-induced unemployment movements").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

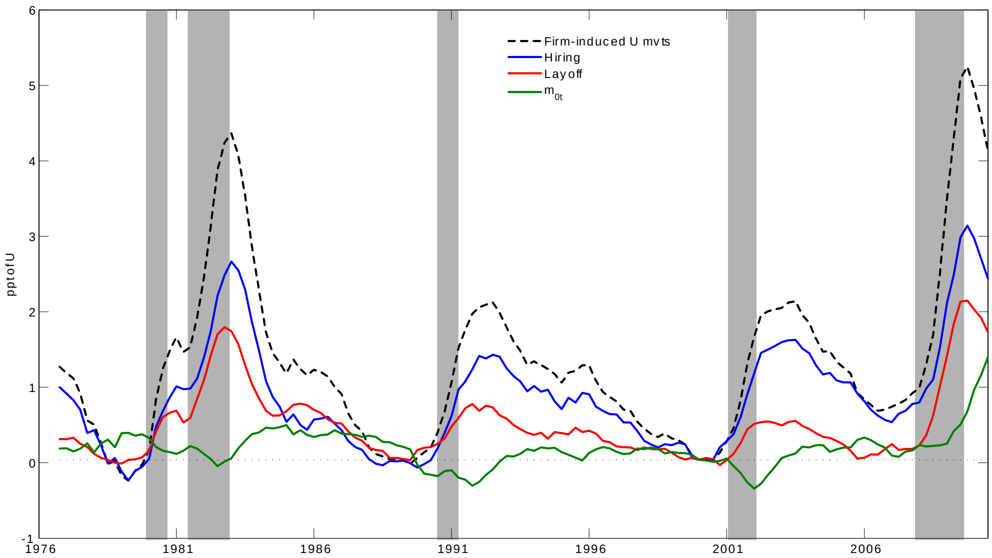
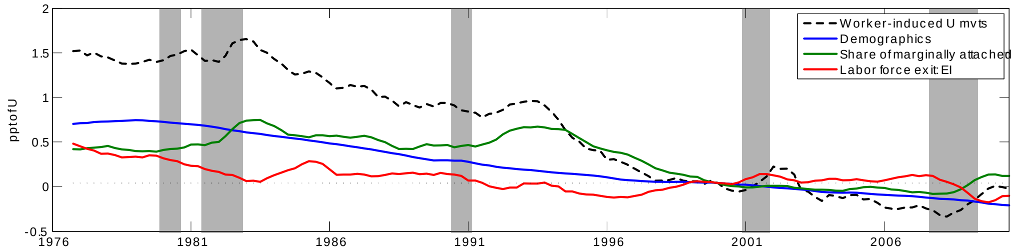


Figure 3: Decomposition of firm-induced unemployment movements into the contributions of hiring, layoffs and changes in matching efficiency. The dashed line is the sum of all three components, 1976-2010. The plotted series are 4-quarter moving averages. For clarity of exposition, the series have been normalized to zero in 2000Q3.



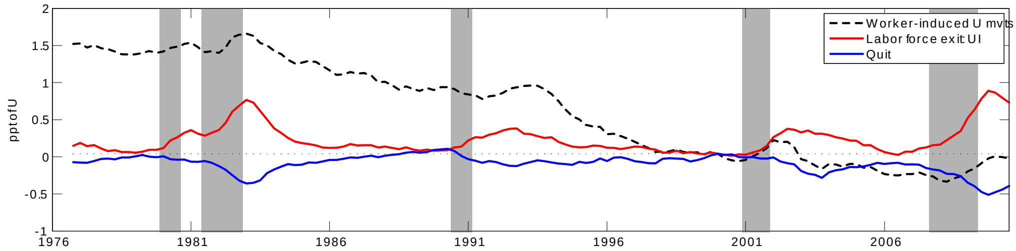


Figure 4: Decomposition of worker-induced unemployment movements into the contributions of quits, composition of the inactivity pool, labor force exit (from UI or EI transitions) and demographics, 1976-2010. The dashed line is the sum of all components. For clarity of exposition, the series have been normalized to zero in 2000Q3. The plotted series are 4-quarter moving averages.

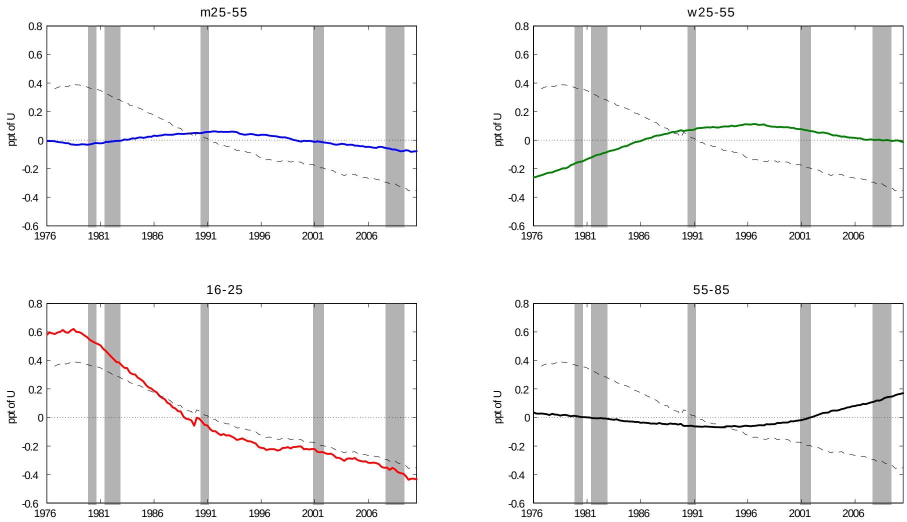


Figure 5: Decomposition of the effect of demographics (due to changes in labor force shares) on unemployment (du_{it}^{demog}) for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of demographics on unemployment, 1976-2010.

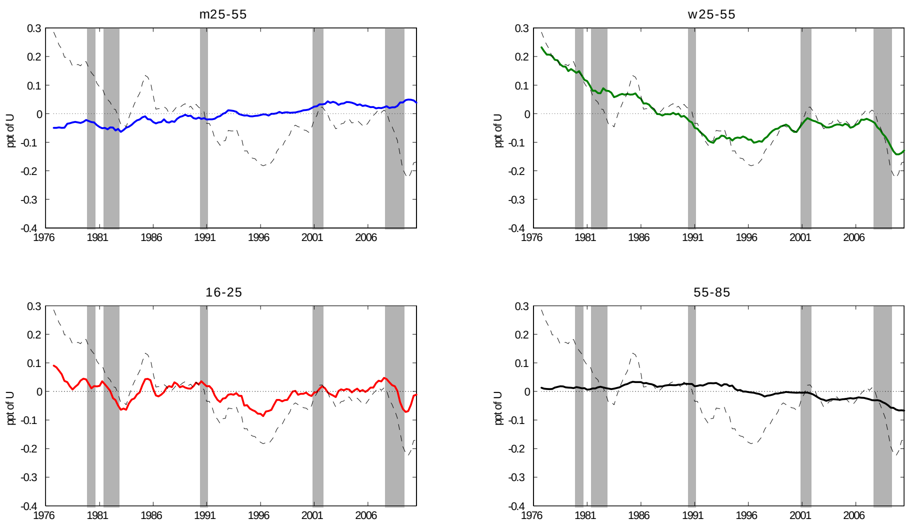


Figure 6: Decomposition of the effect of labor force exit (from employment) on unemployment for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of labor force attachment on unemployment, 1976-2010.

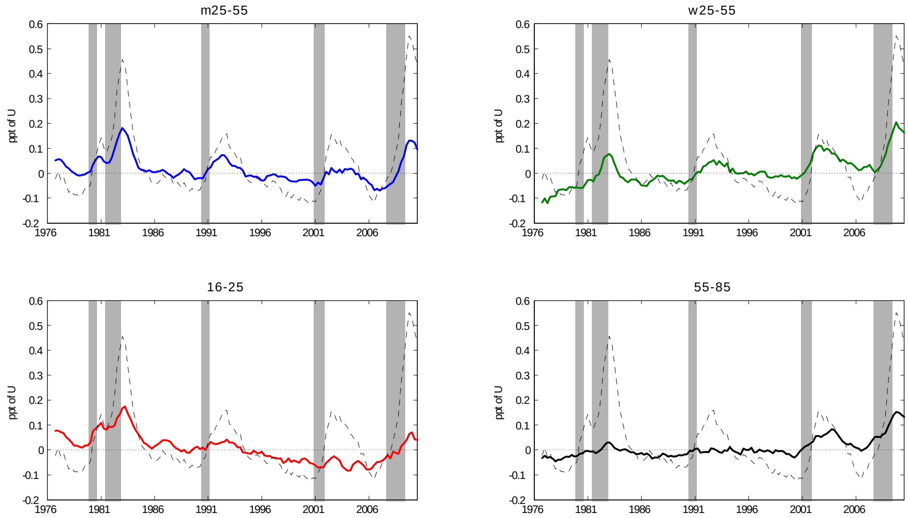


Figure 7: Decomposition of the effect of labor force exit (from unemployment) on unemployment for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of labor force attachment on unemployment, 1976-2010.

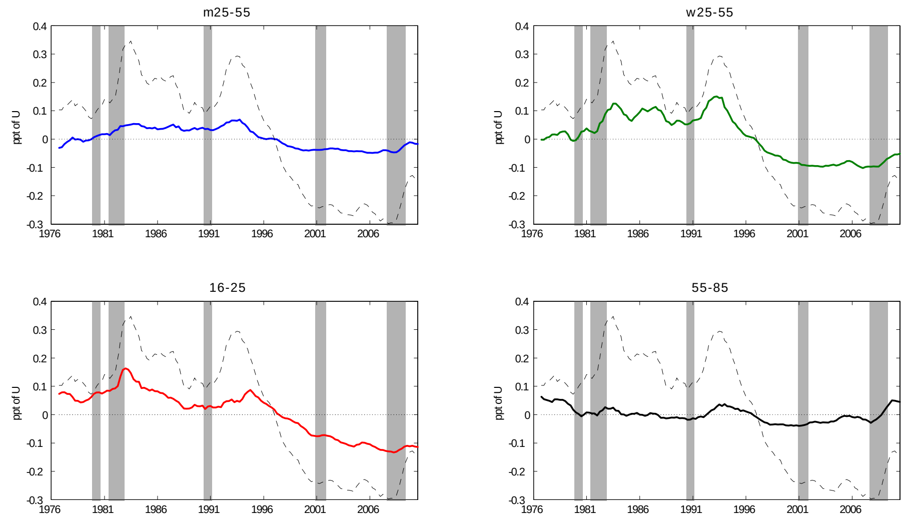


Figure 8: Decomposition of the effect of the composition of the inactivity pool on unemployment (du_{it}^{ILF}) for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of changes in the composition of the inactivity pool, 1976-2010.

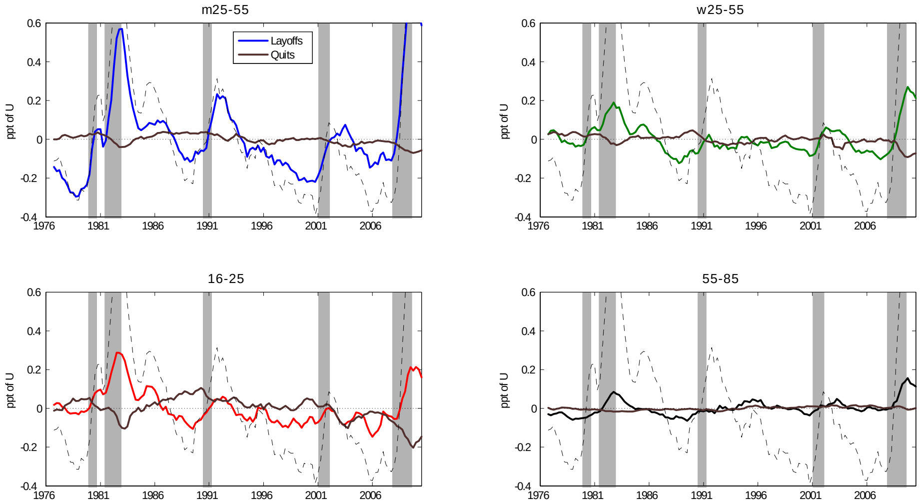


Figure 9: Decomposition of the effect of layoffs and quits on unemployment (du_{it}^{layoff} and du_{it}^{quit}) for four demographic groups (male 25-55, female 25-55, younger than 25, and older than 55). The dashed lines represent the total effect of layoffs and quits on unemployment, 1976-2010.

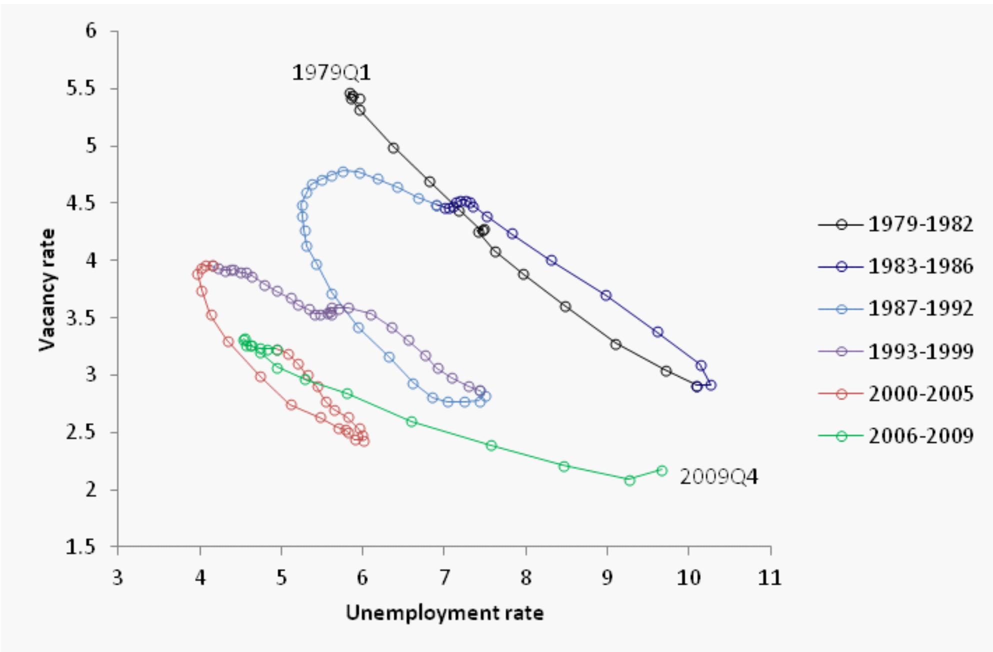


Figure 10: The US empirical U-V locus (the empirical Beveridge curve), 1979Q1-2009Q4. For clarity of exposition, we plot the 4-quarter moving averages of the unemployment and vacancy rates.

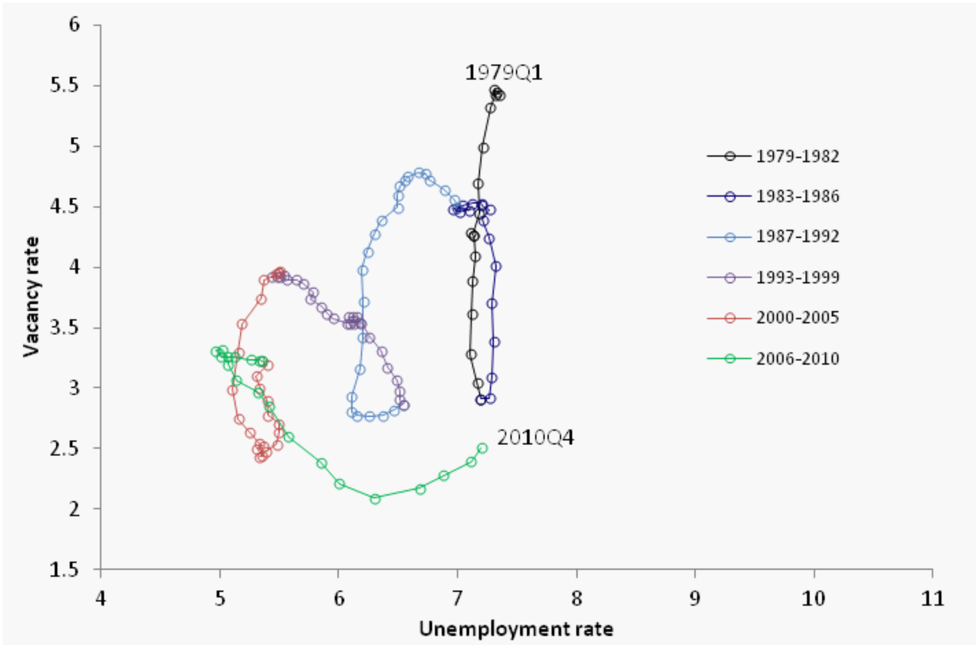


Figure 11: Shifts in the empirical Beveridge curve, 1979-2010. 4-quarter moving averages of the unemployment and vacancy rates.

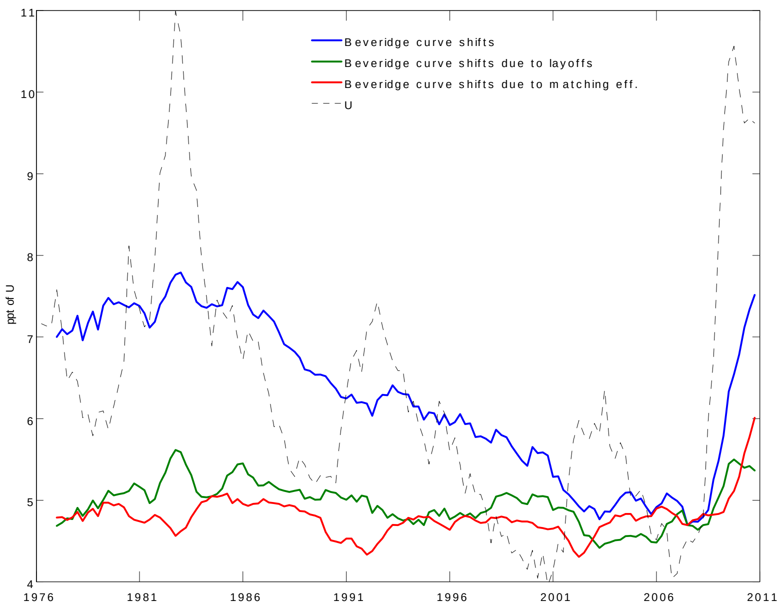


Figure 12: Total Beveridge curve shifts (blue line) and beveridge curve shifts due to layoffs (green line). The dashed line represents stead-state unemployment. 1976-2010.

Table 1: Estimation

Dependent variable:	λ^{UE}	λ^{UE}	$\lambda^{IE\|LF}$
Sample (quarterly frequency)	1967-2010	1967-2010	1976-2010
Regression	(1)	(2)	(3)
Estimation	OLS	GMM	OLS
σ	0.62*** (0.01)	0.61*** (0.01)	--
$a_1(\lambda^{UE})$	--	--	0.23*** (0.01)
$a_2(I^U/I)$	--	--	-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:Q1-2010: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: UI	0.11	0.07	0.14
	LF exit: EI	0.01	0.15	-0.04
	I^U/U { *LM entry: 66%* / *LM exit: 33%*	0.07	0.22	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 $\lambda^{II\text{-}IU}$, and labor market exits (LM exit) from movements in $\lambda^{IU\text{-}II}$ over 1994-2010.

Table 3: Variance decomposition of trend in unemployment *by* demographic group, 1976:Q1-2010:Q4

	Male 25-55	Female 25-55	Young 16-25	Old Above 55
Quits	0.25	0.21	0.60	-0.06
LF exit: EI	-0.27	0.95	0.17	0.15
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. "LF exit: EI" decomposes the contribution of labor force attachment coming from EI transitions only.

Table 4: Variance decomposition of cyclical unemployment *of* demographic groups, 1976:Q1-2010:Q4

	$U^{Male\ 25\text{-}55}$	$U^{Female\ 25\text{-}55}$	$U^{Young\ 16\text{-}25}$	$U^{Old\ 55+}$
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: UI	0.10	0.17	0.11	0.21
LF exit: EI	0.00	-0.06	-0.05	-0.03
I^U/I	0.02	0.08	0.06	0.09
Other	0.02	0.06	0.04	0.04

Note: Each column sum to one. "LF exit: EI" decomposes the contribution of labor force attachment coming from EI transitions only. "LF exit: UI" decomposes the contribution of labor force attachment coming from UI transitions only.