Why did the U.S. unemployment rate used to be so low?[*] (and why it can be very low again)

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Abstract

Using an accounting framework based on a matching function and CPS micro data, we show that the downward trend in US unemployment since the early 80s is driven by (i) the aging of the baby boom generation, although the contribution is smaller than previously thought, and (ii) inactive individuals moving further away from the labor force. These forces are still present today but are masked by exceptionally low hiring and high layoff, forces that have been strictly cyclical over the last 35 years. Our results imply that labor demand explanations of secular unemployment movements are unlikely in the US.

JEL classifications: J6, E24.

1   Introduction

In May 1979, a business cycle peak, the unemployment rate bottomed at 5.6%. Two decades later, in April 2000, another business cycle peak, the unemployment rate bottomed at 3.8%, more than $1\frac{3}{4}$ percentage points (ppt) lower than in 1979. Understanding the origins of such secular movements in unemployment is a central question for economists and policy makers: from a welfare perspective –the unemployment rate captures the fraction of people whose job search is unsuccessful–, or from a monetary policy perspective –the level of unemployment is often believed to help assess inflationary pressures in the economy–.

The literature has proposed a great number of hypotheses to explain secular unemployment movements: changes in demographics, changes in trend productivity growth, changes in the degree of sectoral reallocation, changes in the job search technology, and changes in labor force participation, among others.[1] However, absent a unifying framework to encompass all these explanations, there is yet no consensus on the relative merit of each hypothesis, and hence on the welfare and policy implications of recent secular movements. This paper aims to fill this gap.

In order to help discriminate between these different explanations, we propose a new accounting framework that isolates the contributions of different economic forces to unemployment movements.

Our accounting framework is based on the labor force flows underlying the unemployment rate. Movements in the flows can help discriminate between alternative explanations, because different theories can have different predictions for the flows.[2] However, even a flow decomposition can sometimes provide little guidance to help discriminate between competing theories, and we take on the task to identify the economic mechanisms behind all worker flows. We do so by positing an aggregate matching function and by using information from micro data from

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[1]The aging of the baby boom generation has been proposed to explain the inverse U-shape movement in unemployment since the early 70s (Perry (1970), Flaim (1979), Gordon (1982), Summers (1986), and Shimer (1998, 2001)). Labor demand based explanations coming from changes in trend productivity growth –from low in the 70s to high in the late 90s– include Aghion and Howitt 1994, Mortensen and Pissarides 1998, Ball and Moffitt, 2002, Hornstein, Krusell, Violante, 2007, Pissarides and Vallanti, 2007, Elsby and Shapiro, 2012. Changes in the extent of labor turnover coming from sectoral reallocation (in the sense of Lilien, 1982) or firms' idiosyncratic risk can be found in Davis et al., 2010. Labor supply based explanations include the decline in men's labor force participation (Juhn, Murphy and Topel, 1991, 2002), the increase in women's attachment to the labor force (Abraham and Shimer, 2002), and the rise in disability rolls (Autor and Duggan, 2003). A number of papers highlight the role of labor market institutions and their possible interaction with macroeconomic shocks (e.g., Ljungvist and Sargent 1998, Blanchard and Wolfers 2000). This line of research is most successful at explaining the diverging trends between the US and Europe, a topic outside the scope of this paper.

[2]For instance, a story based on higher trend productivity growth with real wage rigidity (as in Ball and Moffitt, 2002) will generate lower unemployment through more job creation, i.e., more hiring. In contrast, an explanation based on lower labor turnover will generate lower unemployment through a lower job separation rate.

the CPS. We then obtain an approximate decomposition of unemployment into the contributions of different economic forces: hiring, layoff, quit, labor force entry, labor force exit, the demographic composition of the population, the composition of the inactivity pool (the pool of individuals outside the labor force), and changes in matching efficiency –the ability of the labor market to match unemployed workers to jobs–.

We find that the downward trend in unemployment since the early 80s (about -1$\frac{3}{4}$ ppt) is driven by (i) the aging of the baby boom generation, which lowered unemployment by about 0.6ppt, significantly less than previous estimates, (ii) an increase in women's labor force attachment up until the mid 90s, which lowered unemployment by about 0.4ppt, and (iii) since the mid 90s, a downward trend in the fraction of marginally attached individuals, which lowered unemployment by about $\frac{3}{4}$ ppt. Marginally attached individuals are individuals who want to work but are not searching (and are thus *not* considered unemployed).[3] We show that 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 the non-marginally attached.[4]

Since the role played by individuals at the margin of the labor force is substantial after the mid 90s, 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 decreasing interest in market work, as the marginally attached drifted away from the labor force.[5] The decline in the fraction of marginally attached since the mid-90s is widespread across demographic groups or education groups, suggesting a common driving factor behind this trend. We hypothesize that the trend is driven by an added-worker effect (e.g., Lundberg, 1985), in which household secondary workers became more likely to not want to work because the primary worker (the main income earner) saw his real wage increase significantly after the mid-90s. Supporting this hypothesis, we document a striking correlation over 1976-2010 between household income and the fraction of marginally attached. While a theoretical link between productivity growth and the unemployment rate has proved elusive (Blanchard, 2007), our findings raise the possibility

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[3]Non-marginally attached inactives are individuals who do not want a job and are not searching.

[4]It is also true that the marginally attached also have a higher propensity (about 3 times larger) to find a job than the non-marginally attached. However, the marginally attached's propensity to join unemployment is so much higher (about 10 times larger) than that of the non-marginally attached, that a higher fraction of marginally attached raises the unemployment rate.

[5]Although helpful for the intuition, this latter statement is a simplification of reality, because the labor market is not static. Instead, large flows of workers takes place each month between the different labor market states, so that changes in the stock of marginally attached can only be understood by an understanding of the underlying flows. In the paper, we show that the stock of marginally attached declined because of changes in only two flows: (i) more marginally attached gave up any interest in working and became non-marginally attached inactives, *and* (ii) fewer non-marginally attached started to want to work and became marginally attached.

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a new mechanism linking productivity growth and unemployment through an added-worker effect.[6]

In contrast, the component of unemployment driven by hiring and layoffs displays little evidence of a trend and explains little of unemployment's trend. Since labor demand based mechanisms work through changes in firms' hiring and layoff policies, we conclude that labor demand based explanations of unemployment's trend are unlikely in their current form. For instance, an explanation based on higher trend productivity growth and real wage rigidity (Ball and Moffitt, 2002) should have led to higher job creation and hence to a (counterfactual) trend in the hiring component of unemployment. Similarly, an explanation based on less sectoral reallocation (as in Lilien, 1982), on declining intensity of idiosyncratic labor demand shocks (Davis, Faberman and Haltiwanger 2006) or on higher wage flexibility should have led to a lower layoff rate and hence to a (counterfactual) secular decline in the layoff component of unemployment.

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 30 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. Movements along the Beveridge curve, i.e., changes in unemployment due to changes in vacancies, are typically interpreted as cyclical movements in labor demand. Shifts in the Beveridge curve, however, are difficult to interpret. While they are sometimes seen as indicating movements in the level of "equilibrium" or "structural" unemployment, they can in fact be caused by various factors, from cyclical factors, such as changes in the intensity of layoffs, to structural factors, such as demographic changes. Our results imply that the gradual leftward shift in the U-V locus since 1976 owes to the aging of the baby boom generation and to a lower interest in market work, but not to improvements in the efficiency of the matching process or to changes in firms' hiring and layoff policies.

This paper builds on an influential literature that studies the effect of composition of the labor force on secular movements in the unemployment rate.[7] We show that holding labor force shares constant to identify the effect of demographics (a standard approach since Perry,

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[6]Moreover, most theories exploring a link between productivity growth and unemployment have focused on the effect of changes in productivity growth on labor demand, rather than on labor supply as would be the case here. An exception is Elsby and Shapiro (2012).

[7]See,e.g., Perry (1970), Flaim (1979), Gordon (1982), Summers (1986), and Shimer (1998, 2001). Shimer (1998) originally argued that demographics could explain all of the secular movements in unemployment, but the identified contribution of demographics stemmed from two forces: a direct factor –changes in the labor force weights of different groups– and an indirect factor, in which demographic changes affected the youth unemployment rate and *reinforced* the direct effect. However, this indirect effect is very hard to identify. In later work, Shimer (2001) argued that the indirect effect may in fact go the other way and actually partially *offset* the direct effects.

1970) leads to a biased estimate of the contribution of demographics, because labor force shares can, and did, change, when different demographic subgroups experience different trends in their labor force participation rates. This bias is quantitatively important: using labor force shares overestimates the contribution of demographics by about 30%. We also show the importance of another, hitherto unnoticed, composition effect caused by the composition of the inactivity pool: The fraction of inactives who are at the margin of the labor force (and are thus likely to enter unemployment in the future) has a large impact on the level of unemployment. Our finding echoes Hall's (1983) claim that movements in unemployment can be the result of changes in the number of people at the margin of the labor force. However, we find that it is not the number of marginally attached that matters, but instead their share as a fraction of the inactivity pool. And while the number of marginally attached individuals did indeed increase (Juhn, Murphy and Topel, 2002), their share actually declined, bringing the unemployment rate down, rather than up.

By decomposing unemployment into its underlying flows, 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.[8] However, while the focus of that literature was on cyclical frequencies, ours is on secular movements. Moreover, rather than focusing on the flows, our decomposition focuses on the economic decisions behind unemployment movements. The two approaches are related, but our different perspective can provide a number of additional insights, because decompositions between the "Ins" and "Outs" are sometimes hard to interpret and hence provide little guidance to discriminate between competing theories. 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.[9] Moreover, movements in the flows into and out of the labor force are difficult to interpret and yet very important to understand secular unemployment movements. For instance, observing increased flows from out-of-the-labor-force to employment does not tell us whether those increased flows occurred because there are more jobs available, or because more inactive individuals started to search for a job. By addressing such shortcomings, our approach can help discriminate between competing theories.[10]

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[8] See, among others, Blanchard and Diamond (1989, 1990), Bleakley, Ferris and Fuhrer (1999), Shimer (2007), Petrongolo and Pissarides (2008), Elsby, Michaels and Solon (2009), Fujita and Ramey (2009), Elsby, Hobijn, and Sahin (2010, 2011, 2012), Hornstein (2012).

[9] For instance, layoffs are countercyclical, while quits are procyclical (Elsby, Michaels, and Solon, 2009).

[10] In this respect, our approach shares some similarities with the business cycle accounting proposed by

Finally, our paper relates to the literature on the measurement of unemployment and on the difficult distinction between the "unemployment" and "out of the labor force" classifications (Flinn and Heckman, 1983). While there is no consensus on whether one should include the marginally attached or not in the definition of unemployment (e.g., Jones and Riddell 1999), our flow-based decomposition suggests that the distinction is not as important as originally thought: Since the marginally attached are likely to enter unemployment in the future, their presence affects the level of unemployment –even when they are not officially counted as unemployed–. As a result, any unemployment definition will capture the presence of marginally attached.

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 presents the results of our decomposition, Section 5 discusses the implications of our results, Section 6 revisits our unemployment decomposition in Beveridge curve space. Section 7 concludes.

2   Unemployment accounting

This section describes the accounting framework behind our decomposition of unemployment. We proceed in three steps.

First, because the aging of the baby boom is believed to be an important factor behind secular unemployment movements (e.g., Shimer, 1998), we first isolate the contribution of demographics by dividing the working-age population into demographic subgroups.[11] While the literature typically identifies the effect of demographics by holding the demographic composition of the labor force constant, we show that that approach significantly overstates the contribution of demographics, because some of the movements in labor force shares are driven by different trends in the labor force participation rate of the subgroups.

Second, we decompose the unemployment rate and labor force participation rate of each demographic group into their underlying worker flows. Individuals can transit between three labor market states: employment, unemployment and inactivity (i.e., outside the labor force), and the unemployment rate (and labor force participation rate) resulting from these flows is determined by the value of the corresponding transition rates through an accounting identity.

Chari, Kehoe and McGrattan (2007). By focusing on the role played by the different economic decisions, our decomposition is intended to serve as a useful input into the development of models by contrasting the role of different control variables.

[11] Note that following Shimer (1998), we do not control for education since the unemployment rate by education changed over time, making demographic adjustments for education "unwarranted and potentially misleading" (Shimer, 1998). Changes in other demographic characteristics (e.g., race) have had little effect on the unemployment rate (Shimer, 1998), and we abstract from those to minimize sampling error.

Third, because such flow decompositions sometimes provide little guidance to help discriminate between competing theories of unemployment movements, we take on the task to identify the economic mechanisms behind all worker flows. We then obtain an approximate decomposition that allows us to decompose unemployment movements into the contributions of different economic decisions.

2.1 Demographics and composition of the labor force

To isolate the effect of demographics, we divide the population into N demographic (age and sex) groups. In each group, workers can be in one of three labor market states: employment (E), unemployment (U) and inactivity (I). Non-employed individuals are defined as unemployed when they are not searching for a job, while non-employed individuals are considered inactive when they are not searching for a job. In demographic group i, let U_{it}, E_{it}, and I_{it} denote the number of unemployed, employed and inactive, respectively, at instant t. $LF_{it} = U_{it} + E_{it}$ is the size of the labor force in group i, and the unemployment rate is $u_{it} = \frac{U_{it}}{LF_{it}}$.

Denoting $\omega_{it} = \frac{LF_{it}}{LF_t}$ the share of group $i \in \{1, .., N\}$ in the labor force, the aggregate unemployment rate is given by

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

so that differencing gives

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

with u_i and ω_i the average unemployment rate and labor force share of group i.

The literature has traditionally identified the contribution of demographics from $\sum_{i=1}^{N} u_i d\omega_{it}$, i.e., from changes in the labor force shares of different demographic groups.[12] However, changes in the labor force shares can be driven by other factors than demographics. If the labor force participation of one group changes relative to the other groups, the labor force shares can change even though population shares remain constant. To capture the effect of changes in the demographic structure of the population, we instead focus on $\Omega_{it} = \frac{Pop_{it}}{Pop_t}$ the share of group i in the working-age population. We have

$$\omega_{it} = \frac{l_{it}}{l_t} \Omega_{it} \tag{2}$$

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[12] For instance, younger workers have a higher average unemployment rate than older workers, so that, holding age-unemployment rate constant, a lower share of young workers in the labor force will lower the unemployment rate.

with $l_{it} = \frac{LF_{it}}{Pop_{it}}$ the labor force participation rate of group i and $l_t = \sum_{i=1}^{N} \Omega_{it} l_{it}$ the aggregate labor force participation rate. A little bit of algebra combining (1) and (2) shows that changes in the aggregate unemployment rate satisfy

$$du_t = \underbrace{\sum_{i=1}^{N} \beta_i^{\Omega} d\Omega_{it}}_{\text{demographics}} + \sum_{i=1}^{N} \beta_i^l dl_{it} + \sum_{i=1}^{N} \omega_i du_{it} \tag{3}$$

with $\beta_i^{\Omega} = u_i \frac{l_i}{l} - l_i \sum_{k=1}^{N} u_k \Omega_k \frac{l_k}{l^2}$ and $\beta_i^l = \Omega_i \left(\frac{u_i}{l} - \sum_{k=1}^{N} u_k \Omega_k \frac{l_k}{l^2} \right)$ with variables without time subscript referring to time averages.

Expression (3) highlights two important points. First, the effect of demographics on unemployment is given by $\sum_{i=1}^{N} \beta_i^{\Omega} d\Omega_{it}$, but not by $\sum_{i=1}^{N} u_i d\omega_{it}$, because movements in the labor force participation rates of demographic group, l_{it}, affect labor force shares. To show that this distinction is empirically important, Figure 1 compares the contribution of demographics coming from changes in population shares with that coming from changes in labor force shares, the traditional measure of demographics' contribution. Decomposing the working-age population in 8 groups: 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, we can see the labor force shares-based measure overstates (in absolute terms) the contribution of demographics to the secular decline in unemployment by 0.3 percentage point. While changes in labor force shares lead to a 0.9 percentage point decline in unemployment since 1976, the exogenous contribution of demographics is only 0.6 percentage point.

Second, expression (3) makes clear that in order to decompose the aggregate unemployment rate into its underlying flows, we need to decompose not only the unemployment rate of each group but also the labor force participation rate of each group, a problem we now turn to.

2.2 Accounting identities for unemployment and labor force participation

This section presents the concepts of steady-state unemployment and steady-state labor force participation, the accounting identities behind our decomposition of stocks into underlying flows.

2.2.1 Accounting identities by demographic group

Workers can transit between the three labor market states employment (E), unemployment (U) and inactivity (I). 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

$$\begin{cases} \dot{U}_{it} = \lambda_{it}^{EU} E_{it} + \lambda_{it}^{IU} I_{it} - (\lambda_{it}^{UE} + \lambda_{it}^{UI}) U_{it} \\ \dot{E}_{it} = \lambda_{it}^{UE} U_{it} + \lambda_{it}^{IE} I_{it} - (\lambda_{it}^{EU} + \lambda_{it}^{EI}) E_{it} \\ \dot{I}_{it} = \lambda_{it}^{EI} E_{it} + \lambda_{it}^{UI} U_{it} - (\lambda_{it}^{IE} + \lambda_{it}^{IU}) I_{it} \end{cases} \tag{4}$$

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 (Shimer, 2012). 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 we can use the accounting identity

$$u_{it} \simeq u_{it}^{ss} \equiv \frac{s_{it}}{s_{it} + f_{it}} \tag{5}$$

where s_{it} and f_{it} are

$$\begin{cases} f_{it} = \lambda_{it}^{UE} + \lambda_{it}^{UI} \frac{\lambda_{it}^{IE}}{\lambda_{it}^{IE} + \lambda_{it}^{IU}} \\ s_{it} = \lambda_{it}^{EU} + \lambda_{it}^{EI} \frac{\lambda_{it}^{IU}}{\lambda_{it}^{IE} + \lambda_{it}^{IU}} \end{cases} . \tag{6}$$

Expression (5) generalizes the simpler two-state case without movements in-and-out of the labor force where U_{it} satisfies $\dot{U}_{it} = \lambda_{it}^{EU} E_{it} - \lambda_{it}^{UE} U_{it}$ and $u_{it}^{ss} = \frac{\lambda_{it}^{EU}}{\lambda_{it}^{EU} + \lambda_{it}^{UE}}$. With movements in-and-out of the labor force, workers can transition between U and E, either directly (U-E), or in two steps by first leaving the labor force (U-I) and then by finding a job directly from inactivity (I-E). As a result, f_{it}, the unemployment outflow rate that matters for steady-state unemployment rate is a weighted average of λ_{it}^{UE} and $\lambda_{it}^{UI} \lambda_{it}^{IE}$, with weights of 1 and $\frac{1}{\lambda_{it}^{IU} + \lambda_{it}^{IE}}$, the latter being the average time that a worker going U->I->E spends transitioning through state I. s_{it} has a similar expression.

As with the unemployment rate, the steady-state of system (4) provides us with an accounting identity for the labor force participation rate of each demographic group. A little bit of algebra shows that the labor force participation rate of each group is a function of the six transition rates and is given by

$$\begin{aligned} l_{it} \quad &\simeq \quad l_{it}^{ss} \equiv \frac{U_{it} + E_{it}}{Pop_{it}} \\ &= \quad \frac{s_{it} + f_{it}}{s_{it} + f_{it} + \frac{o_{it}}{\lambda_{it}^{IE} + \lambda_{it}^{IU}}} \end{aligned} \tag{7}$$

with $o_{it} = \lambda_{it}^{EU}\lambda_{it}^{UI} + \lambda_{it}^{UE}\lambda_{it}^{EI} + \lambda_{it}^{UI}\lambda_{it}^{EI}$.

2.2.2 An accounting identity for the aggregate unemployment rate

Combining the accounting identities for the unemployment rate (5) and labor force participation rate (7) of each demographic group and aggregating across groups using (3), we obtain an accounting identity for the aggregate unemployment rate.

Taking a Taylor expansion of that identity around the mean of the hazard rates of each demographic group i, we can decompose the aggregate unemployment rate u_t as a function of changes in the hazard rates of each group[13]

$$du_t = d\Omega_t + \sum_x \sum_{i=1}^N \beta_i^x d\lambda_{it}^x + \eta_t \text{ with } x \in \{UE, EU, EI, IE, UI, IU\}, \quad \beta_i^x \in \mathbb{R} \qquad (8)$$

with $d\Omega_t = \sum_{i=1}^N \beta_i^\Omega d\Omega_{it}$ capturing the contribution of demographics and β_i^x the coefficients of the Taylor expansion.

The accounting decomposition (8) is based on exact identities –the definition of steady-state of unemployment and labor force participation–, and is a generalization of the decomposition used in the flow literature (Shimer, 2012), where we allowed for heterogeneity across demographic groups and time-varying group-specific labor force participation rates.

2.3 The economic decisions behind worker flows

To get an idea of the flows behind the secular movements in unemployment, Figure 2 plots the behavior of the six aggregate (i.e., averaged over demographic groups) transition rates over 1976-2010.[14] A number of the transition rates experienced secular movements. First, the EU rate experienced a secular decline. Second, transitions in-and-out-of the labor force have played an important role at low frequencies, with the EI and IU rates experiencing secular declines.

Unfortunately, movements in these flows are not straightforward to interpret and therefore provide little guidance to discriminate between competing theories of unemployment movements. First, an EU transition can occur through a layoff or a quit, with different implications for the economic mechanism at play. Second, movements into the labor force, i.e., IE and IU

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[13]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.

[14]See Section 3 for details on the construction of these series, in particular the correction for the 1994 CPS redesign and the time-aggregation bias correction.

transitions, could be driven by different economic decisions: for instance, how many jobs are available (i.e., the level of hiring) or how many inactive individuals start searching for a job. While the literature on cyclical unemployment fluctuations has generally focused on UE and EU transitions and set aside movements in-and-out of the labor force, this is not possible at low frequencies, since movements in-and-out of the labor force will turn out to be crucial to understand the trend in unemployment.

In this subsection, we thus take on the task to identify the economic mechanisms behind all worker flows. For clarity of exposition, we omit the demographic subscript i in the following discussion, and only explicitly specify the distinction between aggregate and group-specific transition rates when necessary. We successively consider the six flows.

2.3.1 Movements in the job separation rate: layoffs and quits

Using information on the reason for unemployment in the CPS micro data, we can separate movements in the job separation rate λ^{EU} 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 movements in λ^{EU}, we will study separately λ^{EU^l} and λ^{EU^q} with $\lambda^{EU} = \lambda^{EU^l} + \lambda^{EU^q}$, with λ^{EU^l} the hazard rate of moving from employment to unemployment through a layoff and λ^{EU^q} the hazard rate of moving from employment to unemployment through a quit.

We then interpret movements in $\lambda_t^{EU^l}$ as capturing changes in firms' layoff rate (l_t), and movements in $\lambda_t^{EU^q}$ as capturing changes in workers' quit rate (q_t) by making the following approximation:

Approximation 1: $l_t \propto \lambda_t^{EU^l}$ and $q_t \propto \lambda_t^{EU^q}$.

Intuitively, Approximation 1 is saying is that the probability of flowing into unemployment following a layoff is roughly constant over time, so that the layoff rate to unemployment $(\lambda_t^{EU^l})$ is proportional to the layoff rate (l_t) (and similarly for the quit rate). In the online Appendix, we verify Approximation 1 by combining information from the CPS with published data from the BLS Job Openings and Labor Turnover Survey (JOLTS) over 2000-2010. We show that the layoff (quit) rate to unemployment is indeed a constant fraction of the layoff (quit) rate, and that the probability of flowing into unemployment following a layoff (quit) is, to a good approximation, constant over time.

2.3.2 Movements in the unemployed's job finding rate: job creation

As discussed in the introduction, theories linking trend productivity growth to unemployment make strong predictions regarding the rate of job creation.

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To help discriminate between different theories, we extract changes in firms' hiring from movements in the job finding rate. To do so, we assume the existence of a matching function, a device commonly found in macroeconomic models with search and search and matching frictions (e.g., Pissarides, 2000), and relate the flow of new hires from unemployment to the number of job openings and unemployed. Using a standard Cobb-Douglas matching function with constant returns to scale (e.g., Blanchard and Diamond, 1989), we can write

$$m_t = m_{0t} U_t^\sigma V_t^{1-\sigma} \tag{9}$$

with m_t, the number of new hires from unemployment at instant t, V_t the number of vacancies, and m_{0t} aggregate matching efficiency. The aggregate job finding rate of an unemployed is then given by

$$\lambda_t^{UE} = \frac{m_t}{U_t} = m_{0t} \theta_t^{1-\sigma} \tag{10}$$

with $\theta_t \equiv \frac{V_t}{U_t}$ aggregate labor market tightness.

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.[15]

The final step is to incorporate (10) into the accounting identity (8). Expression (8) does not include the aggregate job finding rate λ_t^{UE} but instead the job finding rates λ_{it}^{UE} of each group. Denoting $s_{it}^U \equiv \frac{\lambda_{it}^{UE}}{\lambda_t^{UE}}$ the relative search efficiency of demographic group i, the existence of a matching function implies that the job finding rate of group i is given by $\lambda_{it}^{UE} = s_{it}^U m_{0t} \theta_t^{1-\sigma}$. Log-differencing, changes in job creation can be isolated from movements in θ_t. Movements in m_{0t} and in s_{it}^U captures changes in matching efficiency, and we group these terms under a matching efficiency component of unemployment.

2.3.3 Movements into the labor force: job creation and composition of the inactivity pool

An alternative representation of IE and IU flows

In order to better capture the economic decisions behind the transitions from inactivity to employment (IE) or from inactivity to unemployment (IU), we now consider an alternative, but equivalent, description of the IE and IU flows, that will lend itself more naturally to economic

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[15]In Barnichon and Figura (2011), we study the determinants of movements in m_{0t} over 1976-2010 and find that most of the movements in m_{0t} are driven by changes in the composition of the unemployment pool (in particular, changes in average unemployment duration).

interpretation.

The IE and IU flows can be seen as capturing two steps. First, an individual can decide to look for a job, i.e., "join the labor force".[16] For instance, one can think of an inactive individual going to the job center for the first time. Second, conditional on starting to search, the individual may, or may not, get a job right away, or in our analogy, get a job on his first visit to the job center. If he does, we observe a direct IE transition, and the individual never joins the unemployment pool. If he does not get a job immediately, he joins the stock of unemployed, and we observe an IU transition. The fact that a worker can get a job immediately upon joining the labor force is similar to the idea of stock-flow matching (Coles and Smith, 1998), in which a fraction of the flow of new job searchers is instantaneously matched to the (old) stock of unfilled job openings.[17],[18]

Mathematically, we can rewrite the IE and IU transition rates λ_t^{IU} and λ_t^{IE} in terms of a *labor force entry rate* λ_t^{I-LF} and a *job finding rate conditional on searching* $\lambda_t^{IE|I-LF}$.[19]

Specifically, the measure of individuals who start searching at t is given by $I_t \left(\lambda_t^{IU} + \lambda_t^{IE} \right) dt$, so that we can define the labor force entry rate

$$\lambda^{I-LF} \equiv \lambda_t^{IU} + \lambda_t^{IE}$$

since the number of IE transitions at t is given by $I_t \lambda_t^{IE} dt$, an inactive gets a job immediately

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[16] Following the search literature, we assume that individuals must search to find a job.

[17] As the concept of stock-flow matching makes clear, workers who do find a job instantaneously (the flow matching with the stock) never join the unemployment stock. Hence, the existence of IE transitions is *not* the result of unobserved IU transitions (when data are only available at discrete intervals) and of a time-aggregation bias.

[18] This alternative description of IE and IU flows can easily rationalize the cyclical behavior of IE and IU flows (Figure 2). The IE rate is procyclical (and IU rate countercyclical) because inactive individuals are more likely to get a job immediately upon starting to search, i.e., flow directly into employment, during an expansion (when jobs are plentiful) than during a recession (when jobs are scarce). This also explains why the two rates are strongly negatively correlated.

[19] This description of movements into the labor force can be also be mapped into the recent theoretical framework of Krussel, Mukoyama, Rogerson and Sahin (2012). Although there is no role for search in their framework, workers transiting from I to E also do so in two steps –first, by receiving or not a job offer (at a rate λ using the paper's notation), and then by deciding to participate or not in the labor market (at a rate G given by a decision rule over a distribution of productivity levels z and asset levels a)–, and our description does capture these two steps. Since the IE rate is given by λG and the IU rate by $G(1-\lambda)$, the labor force entry rate G is indeed given by $\lambda^{I-LF} = \lambda^{IE} + \lambda^{IU} = G$, and the job finding rate of an inactive who ends up participating is indeed $\lambda^{IE|I-LF} = \frac{\lambda^{IE}}{\lambda^{I-LF}} = \lambda$. While Krusell et al. impose the same job arrival rate for unemployed and inactive workers ($\lambda = \lambda^{UE} = \lambda^{IE|I-LF}$), we allow for the possibility that λ differs across the two groups, i.e., $\lambda^{IE|I-LF} \neq \lambda^{UE}$.

upon starting to search with hazard rate[20]

$$\lambda_t^{IE|I-LF} \equiv \frac{\lambda_t^{IE}}{\lambda_t^{IE} + \lambda_t^{IU}}.$$

Given the definitions of λ^{I-LF} and $\lambda_t^{IE|I-LF}$, we have $\lambda_t^{IE} = \lambda_t^{ILF}\lambda_t^{IE|I-LF}$ and $\lambda_t^{IU} = \lambda_t^{ILF}(1-\lambda_t^{IE|I-LF})$, and we can rewrite (8) substituting λ_t^{IE} and λ_t^{IU} and obtain the alternative accounting identity

$$du_t = d\Omega_t + \sum_x \sum_{i=1}^N \beta_i^x d\lambda_{it}^x + \eta_t \tag{11}$$

with $x \in \{UE, EU, EI, UI, I-LF, IE|I-LF\}$, $\beta_i^x \in \mathbb{R}$ the coefficients of the Taylor expansion left for the Appendix.

Interpreting movements in λ^{I-LF} and in $\lambda^{IE|I-LF}$

We now turn to our economic interpretation of the transitions into the labor force, i.e., of the movements in λ^{I-LF} and in $\lambda^{IE|I-LF}$.

First, movements in λ^{I-LF} capture inactive individuals' decision to stay inactive or start looking for a job.

Second, we find that movements in $\lambda^{IE|I-LF}$ can be decomposed into three easily interpretable components: (i) movements in $\lambda^{U^{lf}E}$, the job finding rate of labor force entrants, (ii) movements in $\lambda^{U^{lf}I}$, the labor force exit rate of labor force entrants, and (iii) movements in $\frac{I^U}{I}$, the fraction of marginally attached inactive individuals, –individuals who do not look for a job but nonetheless want one (denoted I^U)– in the inactivity pool.

Formally, we can show that, under empirically verified assumptions, there exist constants a_i^{UE}, a_i^{UI}, and a_i^I for each demographic group i such that

Approximation 2:

$$d\ln\lambda_{it}^{IE|I-LF} \simeq a_i^{U^{lf}E} d\ln\lambda_{it}^{U^{lf}E} + a_i^{UI} d\ln\lambda_{it}^{U^{lf}I} + a_i^I d\ln\frac{I_{it}^U}{I_{it}}. \tag{12}$$

The constants a_i^{UE}, a_i^{UI}, and a_i^I can be estimated by regressing $\lambda_{it}^{IE|I-LF}$ on $\lambda_{it}^{U^{lf}E}$, $\lambda_{it}^{U^{lf}I}$ and $\frac{I_{it}^U}{I_{it}}$.

Approximation 2 allows us to identify the economic mechanisms behind movements in $\lambda_{it}^{IE|I-LF}$. First, movements in $\lambda_{it}^{U^{lf}E}$ capture changes in job creation and in matching efficiency.

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[20]With a slight abuse of language given that we are talking in terms of hazard rates, rather than probabilities. In our case, probabilities and hazard rates can be used interchangeably, because of the small values of the transition rates/probabilities λ^{IE} and λ^{IU}.

With an aggregate matching function, we have $\lambda_{it}^{U^{lf}E} = s_{it}^{lf} m_{0t} \theta_t^{1-\sigma}$ with $s_{it}^{lf} \equiv \frac{\lambda_{it}^{U^{lf}E}}{\lambda_t^{UE}}$ the search efficiency of labor force entrants in group i. Changes in job creation can be isolated from movements in θ_t. Movements in m_{0t} and in s_{it}^{lf} captures changes in matching efficiency, and we group these terms under the matching efficiency component of unemployment. Second, movements in $\lambda_{it}^{U^{lf}I}$ capture unemployed workers' decision to continue or stop searching, i.e., labor force exit. Third, movements in $\frac{I_{it}^U}{I_{it}}$ captures changes in the composition of the inactivity pool.

While we leave a formal proof of Approximation 2 for the Appendix, the reasoning behind the approximation is relatively simple:

The starting point is to realize that $\lambda^{IE|I-LF}$, the job finding rate of an individual who just started searching, is the job finding rate of a labor force entrant with an unemployment duration of zero. From the duration dependence literature (e.g., Shimer, 2008),[21] we know that there exists a relation 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. Thus, $\lambda^{IE|I-LF}$ should be related to the job finding rates of labor force entrants $\lambda^{U^{lf}E}$.[22] To illustrate our argument, Figure 3 plots the average conditional job finding rate $\lambda^{IE|I-LF}$ along with $\lambda^{U^{lf}E}$. The two series are highly correlated suggesting a close link between the two concepts. Moreover, consistent with the existence of negative duration dependence, the average job finding rate of an inactive who started to search (and with an unemployment duration of 0) is higher than that of an average unemployed (who has positive unemployment duration).

Finally, the characteristics of the inactives who join the labor force may change over time, so that the relation between $\lambda^{IE|I-LF}$ and $\lambda^{U^{lf}E}$ may change with the composition of the inactivity pool. Indeed, one important dimension of heterogeneity is the inactives' "proximity" to the labor force, with the existence of marginally attached inactives –individuals that are "close" to the labor force, i.e., more likely to enter the labor force in the future–, and the non-marginally attached –far from the labor force, i.e., less likely to enter the labor force– (Jones and Riddell, 1999). As we will show empirically in Section 3, the job finding rate of the marginally attached is very different from that of the non-marginally attached, and changes in the fraction of marginally attached affect aggregate $\lambda^{IE|I-LF}$.[23]

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[21] Duration dependence denotes the phenomenon through which the job finding probability declines with the duration of unemployment either because of unobserved heterogeneity or because of hysteresis/skill depreciation, e.g., Kaitz (1970).

[22] The labor force exit rate of labor force entrants ($\lambda^{U^{lf}I}$) also enters (12), because it affects the rate at which labor force entrants exit unemployment and thus influences the distribution of the labor force entrants by duration of unemployment spell. Since the *average* job finding rate of labor force entrants ($\lambda^{U^{lf}E}$) depends on the duration distribution of the labor force entrants, $\lambda^{U^{lf}I}$ influences the relation between $\lambda^{IE|I-LF}$ and $\lambda^{U^{lf}E}$ and thus enters (12). See the proof in the Appendix for more details.

[23] The pool of marginally attached likely comprises workers who gave up looking because of poor employment

2.3.4 Movements out of the labor force

Movements out of the labor force comprise λ^{UI} and λ^{EI} and capture workers' decision to exit the labor force. First, movements in λ^{UI} capture unemployed workers' decision to continue or stop searching. Second, as Abraham and Shimer (2002), we interpret EI transitions as capturing workers' decision to leave the labor force. In principle, movements in λ^{EI} could also be driven by layoffs, with some workers leaving the labor force following a layoff. However, in the online Appendix, we combine information from the CPS and the JOLTS and find that almost all layoffs end up in unemployment, rather than in inactivity, which implies that EI transitions cannot originate in layoffs.

2.4 A "quasi"-accounting identity for the aggregate unemployment rate

Combining our exact decomposition (11) of unemployment based on stock-flow accounting identities with (10) and Approximations 1 and 2, we obtain an approximate decomposition, or "quasi"-accounting identity, describing the movements in the aggregate unemployment rate. We can then decompose unemployment movements according to[24]

$$
\begin{aligned}
du_t \;=\; & du_t^{demog} + du_t^{hiring} + du_t^{layoff} + du_t^{m_0} \\
& + du_t^{quit} + du_t^{LF\ exit} + du_t^{LF\ entry} + du_t^{I^U} + \mu_t
\end{aligned}
\tag{13}
$$

with du_t^x, $x \in \{demog, layoff, m_0, quit, LF\ exit, LF\ entry, I^U\}$, capturing the changes in unemployment due, respectively, to changes in demographics, hiring, layoffs, matching efficiency, quits, labor force exit, labor force entry, and the fraction of marginally attached (I^U). The expressions for the du_t^x term are shown in the Appendix.

The error term μ_t includes the 2nd-order approximation error of the Taylor expansion and the approximation errors from Approximation 1 and 2. Importantly, we will show that our approximate decomposition of unemployment, (13), is a very good approximation, and that the contribution of μ_t is small.

Thanks to this linear decomposition, we can then assess the separate contributions of each

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prospects. In contrast, the pool of non-marginally attached likely includes higher quality people, who decided not to work but who could easily find a job if they wanted to. As a result, the job finding rate (conditional on starting to search) of the two groups can be very different.

[24]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 and hence allows us to analyze low-frequency movements. To guarantee that the approximation remains good however, we take a second-order approximation, which performs extremely well, as we will see in Figure 5. The expressions for each component are shown in the online Appendix.

economic concept by noting as in Fujita and Ramey (2009) that

$$Var\,(y+z) = Cov(y, y+z) + Cov(z, y+z) \tag{14}$$

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

3 Estimation

This section presents the empirical steps behind our unemployment decomposition: first, the estimation of the transition rates, second, the estimation of a matching function, and third, the estimation of Approximation 2, i.e., the decomposition of the inactives' job finding rate. Previewing the important role played by the marginally attached, we estimate the transition rates in and out of marginal attachment and discuss how the fraction of marginally attached in the inactivity pool affects the unemployment rate.

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.[25] The estimated transition probabilities suffer from time-aggregation bias because one can only observe transitions at discrete (in this case, monthly) intervals (Shimer, 2012).[26] 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. Extending Shimer (2012), 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.[27] 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,

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

[26] Another issue is classification error (Abowd and Zellner, Poterba and Summers, 1986). Although it is not clear whether one should apply these correction methods on the current CPS survey, Elsby, Hobijn and Sahin (2012) try different correction methods, and the secular trends are broadly unchanged.

[27] To address Shimer's (2012) 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).

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 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:

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

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

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

using our measure of the job finding rate λ^{UE} as the dependent variable.[28] With $\ln m_0$ the intercept of the regression, aggregate matching efficiency is then given by $\ln m_{0t} = \ln m_0 + \zeta_t$. We estimate (16) with monthly data using the composite help-wanted index presented in Barnichon (2010) as a proxy for vacancy posting.[29] 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.

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[28] 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.

[29] 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 JOLTS. See Barnichon (2010) for more details.

3.3 Decomposing the inactive's job finding rate

To decompose movements in $\lambda^{IE|I-LF}$, we proceed as described in Section 2 and estimate, for each demographic group i, the relation

$$\ln \lambda_{i,t}^{IE|I-LF} = a_{i,0} + a_i^{U^{lf}E} \ln \lambda_t^{U^{lf}E} + a_i^{UI} \ln \lambda_{i,t}^{U^{lf}I} + a_i^I \ln \frac{I_{i,t}^U}{I_{i,t}} + \varepsilon_{i,t}. \tag{17}$$

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?".[30] For clarity of exposition, column (3) of Table 1 presents only the results of a regression using aggregate hazard rates, but separate regressions for each demographic group yield similar conclusions. All coefficients come out highly significantly, and Approximation 2 is good, as the regression explains 86% percent of the variance of $\lambda^{IE|I-LF}$.[31]

The effect of the marginally attached on the unemployment rate can be seen from the negative coefficient in front of $\frac{I^U}{I}$: an increase in the share of marginally attached individuals reduces the average (conditional) job finding rate of the inactives, and, through (5), increases the unemployment rate.

3.4 Marginally attached vs. non-marginally attached

This last result highlights the effect of the fraction of marginally attached on the level of unemployment. Previewing the large role played the marginally attached in explaining unemployment's trend, we seek to better understand the difference between a marginally and a non-marginally attached. To do so, we exploit the redesign of CPS in 1994 and separately measure the transition rates of the marginally attached and non-marginally attached over 1994-2010.[32] As shown in Figure 4, the marginally attached have a much higher propensity λ^{IU} to join unemployment than the non-marginally attached (about 10 times higher), but their (unconditional) propensity λ^{IE} to find a job is only 3 times higher. As a result, their conditional job finding rate $\lambda^{IE|I-LF} = \frac{\lambda^{IE}}{\lambda^{IE} + \lambda^{IU}}$ is lower than that of the non-marginally attached, and a higher share of marginally attached lowers aggregate $\lambda^{IE|I-LF}$ (as captured by regression

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[30]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.

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

[32]Specifically, after the CPS redesign in 1994, the question "Do you currently want a job now, either full or part-time?" is asked to all rotation groups, allowing us to observe the labor market transitions of the marginally attached, and thus allowing us to measure separate worker flows for marginally and non-marginally attached inactives. Before 1994, the question was only asked to the *outgoing* rotation groups and thus does not allow measurement of the flows in and out of I^U or I^I.

(17)), which, through (5), increases the unemployment rate.[33]

4   A decomposition of unemployment

After verifying the quality of the approximation underlying our unemployment decomposition, this section presents our main results and discusses their implications for theories of secular unemployment movements.

4.1   The quality of the approximation

Before discussing our results, it is important to verify that our approximate unemployment decomposition, equation (13), does indeed capture, to a good approximation, the movements in unemployment. Figure 5 plots, in dashed red, the steady-state unemployment rate along with, in plain black, the unemployment rate implied by (13).[34] We can see that our approximate decomposition does an excellent job at capturing unemployment movements. A variance decomposition exercise confirms this impression, and Table 2 shows that the contribution of the approximation error (labelled μ_t in (13) and referred to as "Other" in Table 2) to the variance of unemployment only amounts to 2 percent.

4.2   The trend-cycle dichotomy

Using (13), we decompose unemployment movements into the contributions of six components: hiring, layoff, matching efficiency, quit, labor force exit, labor force entry, fraction of marginally attached in the inactivity pool and demographics (age/sex). To summarize our results graphically, we group these components under a firm component (hiring and layoff) and a worker component (quit, labor force exit and entry, fraction of marginally attached and demographics).

Figure 5 plots the unemployment rate along with its worker component and illustrates our first main result. The trend in unemployment is driven by secular movements in the worker

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[33]While formalizing the mechanism behind the different employment prospects of marginally and non-marginally attached individuals is outside the scope of this paper, one can think of marginally attached as individuals with a low utility of inactivity (relative to activity) and non-marginally attached as individuals with a high utility of inactivity. If individuals are heterogeneous in terms of search efficiency (perhaps because of different productivity levels) and search is costly, only the most search efficient inactives will search for a job. For individuals with a low utility of inactivity (the marginally attached), even individuals with a low search efficiency draw will start searching and the observed job finding rate will be low. In contrast, for individuals with a high utility of inactivity (the non-marginally attached), only individuals with a high search efficiency parameter will decide to search, and the observed job finding rate will be high.

[34]As shown in Shimer (2012), the steady-state unemployment rate is an excellent approximation of the actual unemployment rate.

component, which lowered unemployment by about $1\frac{3}{4}$ ppt since the early 80s, but not by secular movements in hiring and layoffs. At business cycle frequencies, the opposite is true with hiring and layoff accounting for most of cyclical movements in unemployment. The U.S. labor market thus seems to be characterized by a trend-cycle dichotomy, in that different forces seem to drive the cycle and the trend.

A variance decomposition using (13) confirms this impression, and Table 2 shows that most of the trend in unemployment since 1976 is the result of changes in demographics and in the fraction of marginally attached.[35] In contrast, about 90% of cyclical fluctuations in unemployment are the result of hiring and layoff.

Studying the components of unemployment in more detail, Figure 6 focuses on the firm components of unemployment and presents the contributions of hiring, layoff and matching efficiency to unemployment movements, with the dashed black line capturing the sum of these three factors. After controlling for demographic changes, the component of unemployment driven by hiring and layoffs shows little evidence of a trend (Figure 6), and Table 2 confirms that hiring and layoffs only account for a small fraction of unemployment movements at low-frequencies.[36] While changes in matching efficiency can have a non-trivial cyclical effect on unemployment –for instance, lower matching efficiency increased unemployment by about 1.5 ppt in end 2010–, matching efficiency shows little evidence of secular movements.[37]

Figure 7 decomposes the worker component –the dashed black line– into its individual components: demographics, fraction of marginally attached, labor force exit, labor force entry, and quit. We can see that the trend in unemployment is due to three forces: (i) changes in demographics, (ii) until the mid-90s, changes in labor force attachment, and (iii) since the mid-90s, a decline in the share of marginally attached individuals in the inactivity pool. Table 2 confirms this visual inspection, and the three factors explain virtually all of the variance of the trend in unemployment.[38]

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[35] 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 (13) to each frequency range.

[36] While the aggregate job separation rate λ_t^{EU} displays a downward trend, it is entirely due to the aging of the baby boom and to the existence of a slight trend in quits to unemployment. Once we exclude these two aspects (as we do in Figure 6) and isolate movements in the layoff rate, there are no secular movements left. Note that, in line with 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.

[37] In Barnichon and Figura (2011), we show that matching efficiency movements capture mostly changes in the composition of the unemployment pool, with the average "quality", or employability, of the pool deteriorating following recessions and only recovering slowly over expansions.

[38] The other worker components (labor force entry and quit) have had no discernible effect on unemployment's trend. The small contribution of labor force entry comes from the fact that labor force entry (λ^{I-LF}) does not enter the expression for steady-state unemployment (5), and thus only affects the aggregate unemployment rate through the (indirect and small) effect of labor force participation rate on labor force shares (as can be seen

Looking more closely at the worker components, Figure 7 shows that demographics and the aging of the baby boom lowered the unemployment rate by about 0.6 percentage point over 1980-2010, significantly less than previous estimates.[39] Younger workers have higher turnover and a higher unemployment rate than prime age or old workers, and a decline in the youth share automatically reduces the aggregate unemployment rate.[40]

Changes in labor force attachment, i.e., changes in the propensity of workers to leave the labor force, lowered the unemployment rate by about 0.4 percentage point until the mid 90s. As shown in the online Appendix, the contribution of labor force attachment is driven by one particular demographic group, prime-age women, whose rate of turn-over between employment and inactivity (EI transitions) progressively declined until the mid 90s (Abraham and Shimer, 2002). Ceteris paribus, a lower EI rate raises the ratio of employed individuals to inactive individuals, which lowers the unemployment rate, because employed individuals are less likely to enter the unemployment pool than inactive individuals (i.e., $\lambda^{EU} < \lambda^{IU}$ as shown in Figure 2).

Finally, 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. Given the importance of this new mechanism, we postpone a detailed exploration of this trend to next section.

4.3   Discriminating between competing theories

We now discuss the implications of our decomposition for popular theories of secular unemployment movements.

A first implication of our results is that standard labor demand explanations of the trend in US unemployment since the early 80s are unlikely in their current form: According to a standard search and matching model, an explanation based on higher trend productivity growth should have led to higher job creation and higher equilibrium labor market tightness and hence to a trend in the hiring component of unemployment. However, we find no evidence of a trend in the component of unemployment driven by job creation. Similarly, explanations based on less sectoral reallocation, declining intensity of idiosyncratic labor demand shocks or higher wage flexibility should have led to fewer layoffs and hence to a secular decline in the layoff component of unemployment. However, we find no evidence of a trend in the component

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from (3)).

[39] As shown in Figure 1, the traditional approach based on holding labor force shares fixed would imply that demographics lowered unemployment by 0.9 percentage point over 1980-2010. In the literature, Shimer (1998) estimates that the aging of the baby boom lowered unemployment by 0.8 percentage point over 1978-1998.

[40] See the online Appendix for a disaggregation of the demographic contribution by demographic groups and evidence that the decline in the youth share is behind the contribution of demographics.

of unemployment driven by layoffs.[41] Finally, the fact that we find no trend in matching efficiency suggests that there has been no significant improvement in the efficiency of the matching process in the U.S. labor market.

Instead, our results point to theoretical directions involving workers' labor supply decision: the trend in unemployment owes to women's lower rate of turn-over in and out of the labor force, and to a decline in the fraction of marginally attached, i.e., a decline in the fraction of inactives at the margin of the labor force, a topic to which we turn next.[42]

5 The disappearing marginally attached

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. Since the contribution of the marginally attached to unemployment's trend is substantial, and as far as we know, previously undocumented, we now explore the reasons for this trend.

A number of hypotheses could explain the decline in the fraction of marginally attached. A first possibility is that the marginally attached found jobs and joined the labor force (in greater proportion than the non-marginally attached) after the mid-90s thanks to the high-tech boom and good labor market prospects. A second possibility is that the marginally attached did the exact opposite and left the labor force altogether by simply giving up any interest in working, for instance because of a wealth effect through the increase in networth after the mid-90s, or through an added-worker effect driven by strong wage growth after the mid 90s.[43]

To help discriminate between alternative explanations, we do two things. First, we show that the decline in the fraction of marginally attached is not driven by any particular subgroup, defined either by demographic (age and sex) or education. Second, and in the spirit of this paper, we extend our stock-flow decomposition based on (4) from three to four states (by

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[41]Our results also have implication for related debates on the declining rate of job turnover (Davis, Faberman and Haltiwanger, 2006, Davis et al. 2010) and on secular changes in the rate of job loss, or job instability (Gottschalk and Moffitt, 1999, Farber, 2007, Davis, 2008). Consistent with Farber (2007), we find no trend in the rate of job loss or job instability, once we control for demographics. Moreover, the fact that demographics accounts for the decline in turn-over may be related to Jaimovich and Siu (2009) finding that the aging of the labor force accounts for a significant fraction of the decline in postwar business cycle volatility since the late 70s.

[42]The decomposition of the worker component of unemployment also provides a number of implications for labor-supply explanations of unemployment's trend that we discuss in the Appendix, specifically, the decline in prime-age men labor force participation rate (Juhn, Murphy and Topel 1991, 2002) and the increase in disability rolls (Autor and Duggan 2003).

[43]The added-worker effect refers to the mechanism through which the secondary worker in a household can be more or less likely to want to work (or more generally participate in the labor market) depending on the labor market status and income of the household's primary worker. The wealth effect refers to the mechanism in which changes in household networth makes the secondary worker more or less likely to want to work. (see e.g., Pissarides, 2000).

dividing the inactivity pool into marginally and non-marginally attached) and decompose $\frac{I^U}{I}$ into its underlying worker flows.

5.1 The marginally-attached across subgroups

We now show that the decline in the fraction of marginally-attached after the mid 90s is widespread across demographic or education subgroups, except for older workers.

First, Figure 9 plots the behavior of $\frac{I^U}{I}$ for four demographic subgroups: Prime-age male 25-55, Prime-age female 25-55, Younger than 25 and Over 55. Prime-age males and females display remarkably similar behavior, suggesting a common force behind these movements. The behavior of the younger than 25 is similar with a strong downward trend since the mid 90s, although a secular trend can also be observed in the early 80s.

Interestingly, the fraction of marginally attached is countercyclical, i.e., there are more inactives at the margin of the labor force in recessions, a fact that we return to in Section 5.3, when we consider one possible explanation for the movements in $\frac{I^U}{I}$.

Second, Figure 10 looks at the behavior of $\frac{I^U}{I}$ for three education groups: High school or less, Some college or associated degree, Bachelors or higher degree. All three groups display a decline in the fraction of marginally-attached that started in the mid-90s, although the decline appears somewhat stronger, and started earlier, for less educated individuals.

5.2 A flow decomposition of $\frac{I^U}{I}$

The widespread decline in the fraction of marginally-attached after the mid-90s across different categories of individuals suggest a common driving factor behind this trend. To help discriminate amongst alternative explanations, we identify the labor force flows behind the movements in $\frac{I^U}{I}$.

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. Specifically, we decompose the stock $\frac{I^U}{I}$ into the contributions 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

$$d \ln \frac{I^U_t}{I_t} \simeq \sum_{A \neq B} \gamma^{AB} d \ln \lambda^{AB}_t \tag{18}$$

with $A, B \in \{E, U, I^U, I^I\}$ and $\{\gamma^{AB}\}$ the coefficients of the log-linearization.

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While decomposition (18) can appear cumbersome, our results are surprisingly simple, and we find that

$$d \ln \frac{I_t^U}{I_t} \simeq \gamma^{I^U I^I} d \ln \lambda_t^{I^U I^I} + \gamma^{I^I I^U} d \ln \lambda_t^{I^I I^U} \qquad (19)$$

so that only two hazard rates matter for the behavior of $\frac{I^U}{I}$ since the mid-90s: $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$. Specifically, a variance decomposition exercise shows that $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$ account for, respectively, 73% and 30% of the variance of $\frac{I_t^U}{I_t}$ (Table 2 or Table A2 in the Appendix).[44]

This decomposition yields an important result: the fraction of marginally attached declined, not because the marginally attached joined the labor force (by finding jobs or joining the unemployment pool), but instead because the inactives drifted further away from the labor force. Recall that $\lambda^{I^I I^U}$ captures the propensity that a non-marginally attached starts wanting a job, and that $\lambda^{I^U I^I}$ captures the propensity that a marginally attached) active stops wanting a job. These two hazard rates, plotted in Figure 8, show the same conclusion –the inactives became less interested in market work–: compared to the mid 90s, (i) the marginally attached now have less interest in working and more of them become non-marginally attached ($\lambda^{I^U I^I}$ increased), and (ii) the non-marginally attached now have less interest in working and fewer of them become marginally attached ($\lambda^{I^I I^U}$ decreased).

5.3 Lower interest in market work and added-worker effect

While a detailed exploration of the reasons behind the lower interest in market work is beyond the scope of this paper, we can speculate about a possible economic force behind this trend.

In particular, if an added-worker effect is behind the decline in the fraction of marginally attached after the mid 90s, we should observe a similar, but mirror-image, trend in the real income of households: As households' labor income increased, the incentive for secondary household worker to worker diminished and lead to a decline in the fraction of marginally attached. Figure 11 plots the real median family income over 1976-2010 along with the fraction of marginally attached (on a negative scale).[45] The correlation between the two series, both at low and cyclical frequencies, is striking, with both series displaying a secular shift starting in the mid-90s, and a Granger causality test shows that income Granger-cause the fraction of marginally attached.[46] Interestingly, not only the trend but also the cyclicality of the share of

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[44] The online Appendix confirms this result visually by plotting the movements in I^U/I along with the movements in I^U/I generated solely by movements in $\lambda^{I^U I^I}$ and $\lambda^{I^I I^U}$. While the variance decomposition reported in Table 2 is for unfiltered data, the variance decomposition is similar at low and cyclical frequencies.

[45] Using the bottom quartile instead of the median yields similar results. Data on family income are taken from CPS Annual Social and Economic Supplement microdata. Data are inflated to 2011 dollars using the CPI-U-RS. Using instead real earnings per hour from the CPS Merged Outgoing Rotation Group gives a similar result.

[46] The correlation is -0.95. We can reject that the fraction of marginally attached Granger-cause income

marginally attached is consistent with an added-worker effect: the share of marginally attached increases in downturns because real household income declines, which raises the incentive of secondary workers to participate in the labor market.

While this correlation is only indicative, it suggests a promising avenue for future research on a link between productivity growth and unemployment: the faster productivity growth of the late-90s could have led to a significant increase in real wages, which through an added-worker effect, lowered labor supply, i.e., the number of people interested in working, and thus lowered the aggregate unemployment rate.[47] Unlike standard explanations linking productivity growth and unemployment, the effect of faster productivity growth need not have occurred through firms' labor demand response, but rather through (secondary) workers' labor supply response.

6 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 thus 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 12) in light of our findings, and study why the U-V locus progressively shifted to the left since 1976.

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

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

(p-value <0.01) but cannot reject that income Granger-cause the fraction of marginally attached.

[47]Note that, in theory, the effect (sign and strength) of an increase in household income on the secondary worker's labor supply depends on the relative strengths of the income and substitution effects, as well as the relative price and effectiveness of alternatives to market work (Lundberg, 1985).

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

Using our unemployment decomposition (13), it is possible to identify the components of unemployment responsible for the shifts in the Beveridge curve. To do so, we regress each component of unemployment on labor market tightness, i.e., we estimate

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

with $x \in \{demog, \, layoff, \, quit, \, LF\_I, \, I^U/I, \, m_0\}$ and ε_t^x capturing the Beveridge curve shifts caused by each component. Collecting all the ε_t^x together, we then get the total shifts in the Beveridge curve $\varepsilon_t = \sum_x \varepsilon_t^x$.

Figure 13 plots the total Beveridge curve shifts ε_t along with the shifts generated solely by layoffs (ε_t^{layoff}) as well as the shifts generated solely by matching efficiency ($\varepsilon_t^{m_0}$). As can be seen from Figure 13, the secular leftward shift cannot be explained by shifts due to layoffs or matching efficiency. Instead, the secular shift in the empirical Beveridge curve over the last 35 years is driven by changes in demographics and labor supply changes: A variance decomposition exercise of $\varepsilon_t = \sum_x \varepsilon_t^x$ shows that shifts due to layoffs explain only 13% of the total shifts in the Beveridge curve, but that demographics account for 37%, the fraction of marginally attached 32% and labor force attachment 14%.

7   Conclusion

This paper uses a new accounting framework to help discriminate between different theories of secular unemployment movements. We find that most of the downward trend in US unemployment since the early 80s can be attributed to the aging of the baby boom and to a downward trend in inactive individuals' interest in market work, but not to trends in hiring and layoff.

These results have strong implications for current theories of secular unemployment movements in the US. Labor demand explanations are unlikely in their current form, and successful theories should account for the behavior of individuals at the margin of the labor force and for changes in individuals' willingness to work, i.e. in the economy's labor supply.[48] We suggest a possible route for future research by highlighting a possible mechanism linking productivity growth and unemployment through an added-worker effect. In particular, we document a striking correlation between household income and the fraction of individuals at the margin of

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[48] See Garibaldi and Wasmer (2005), Haefke and Reiter (2006), and more recently Krussel, Mukoyama, Rogerson and Sahin (2011, 2012) for very promising efforts to understand the role of labor supply at business cycle frequencies.

the labor force.

Interestingly, the forces that drove the unemployment rate to a 40 year low of 3.8% in April 2000 are still present today: the population is just as old, and the fraction of marginally attached is only slightly lower. However, these forces are masked by an exceptionally low hiring rate, high layoff rate and low matching efficiency, forces that have been strictly cyclical over the last 35 years. Extrapolating this pattern forward, we can speculate about a future unemployment rate bottoming at 3.8% at the next business cycle peak.

Our unemployment accounting framework can be applied to other countries where vacancy data and labor force surveys data are available, such as Germany, France, Japan, or the UK. These countries experienced different secular trends in their unemployment rate and unemployment flows (Rogerson and Shimer, 2010), and understanding the sources of these trends, such as the decline in UK unemployment after the early 90s or the exceptional performances of the German labor market in the last ten years, would be particularly interesting projects.

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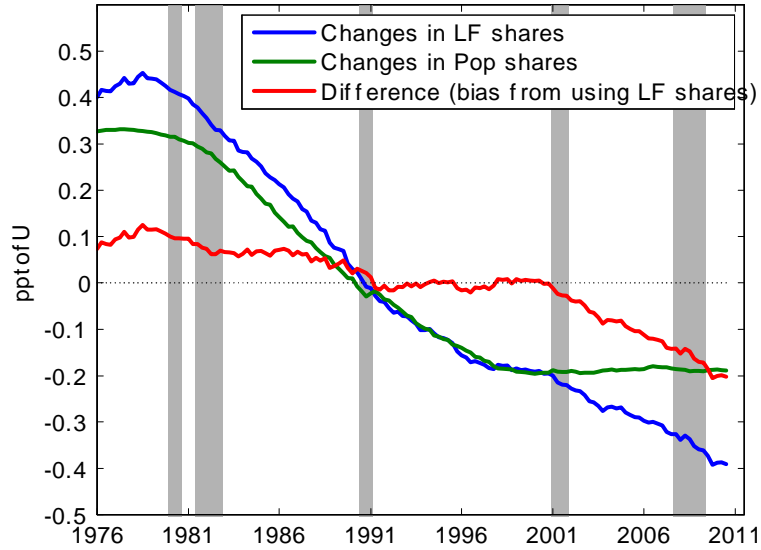
Figure 1: Contribution of demographics to movements in unemployment. Blue line: contribution of changes in labor force shares. Green line: contribution of changes in population shares. Red line: difference between blue and green line, 1976-2010.
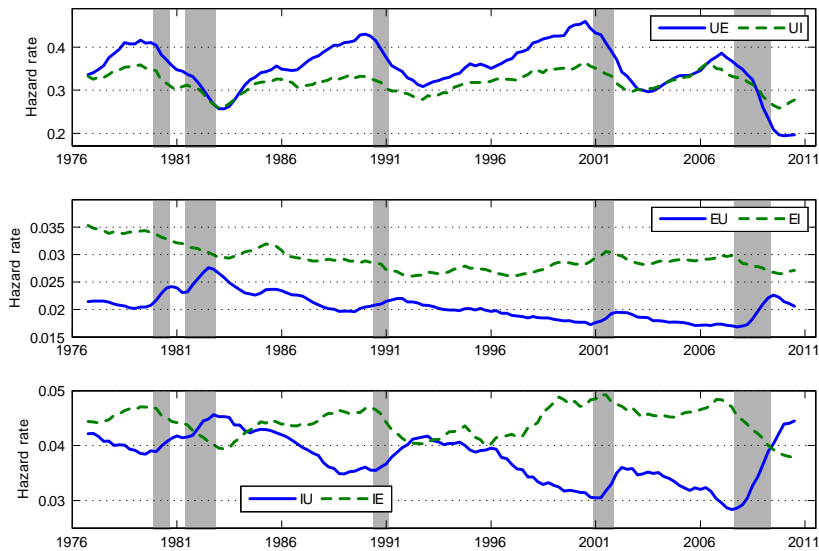
Figure 2: The six transition rates between Unemployment, Employment and Inactivity, 1976-2010. The plotted series are 4-quarter moving averages.
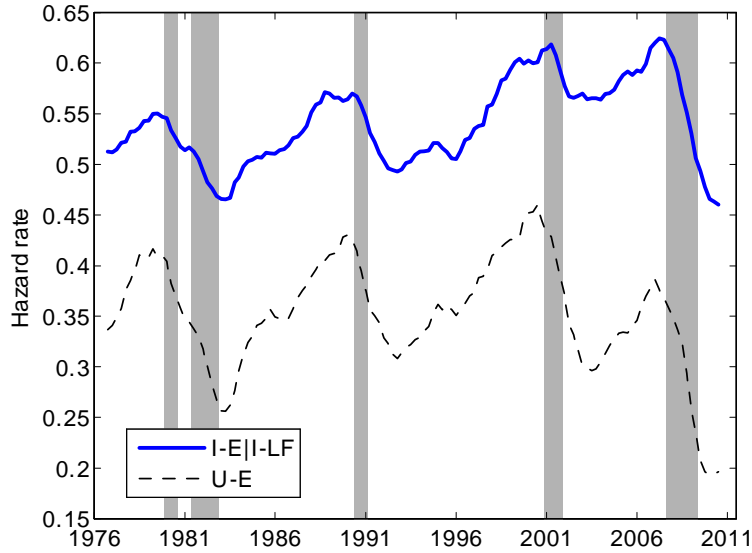
Figure 3: Job finding rate of inactives conditional on joining the labor force ($\lambda^{IE|I-LF}$) and job finding rate of unemployed labor force entrants. 4-quarter moving averages, 1976-2010.
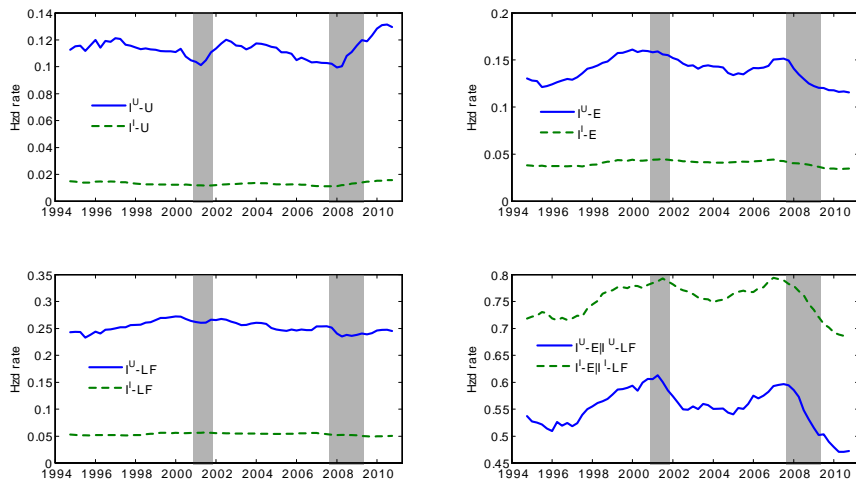
Figure 4: Transition rates into the labor force for marginally attached (plain blue line) and non-marginally attached (dashed green line) individuals. The upper-left panel plots the IU rate, the upper-right the IE rate, the bottom-left the I-LF rate and the bottom-right the job finding rate conditional on searching (IE|I-LF). 4-quarter moving averages, 1994-2011.
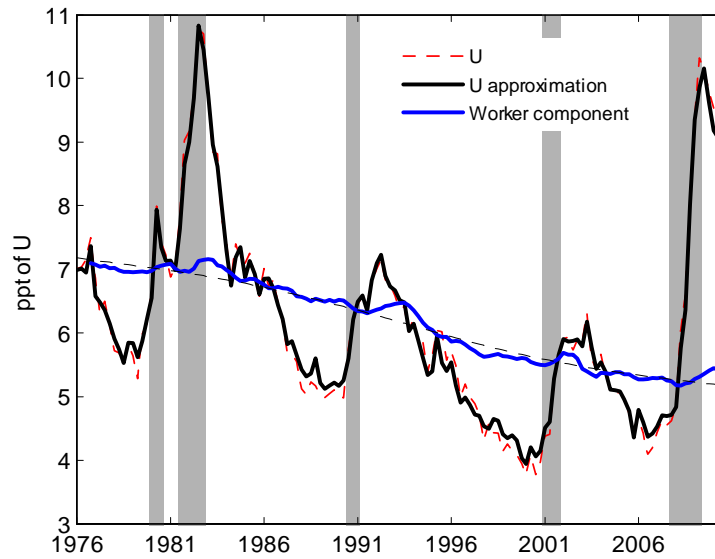
Figure 5: Steady-state unemployment (dashed red line), unemployment from approximate decomposition (black line), and worker component of unemployment (demographics, labor force entry/exit, fraction of marginally attached and quits).
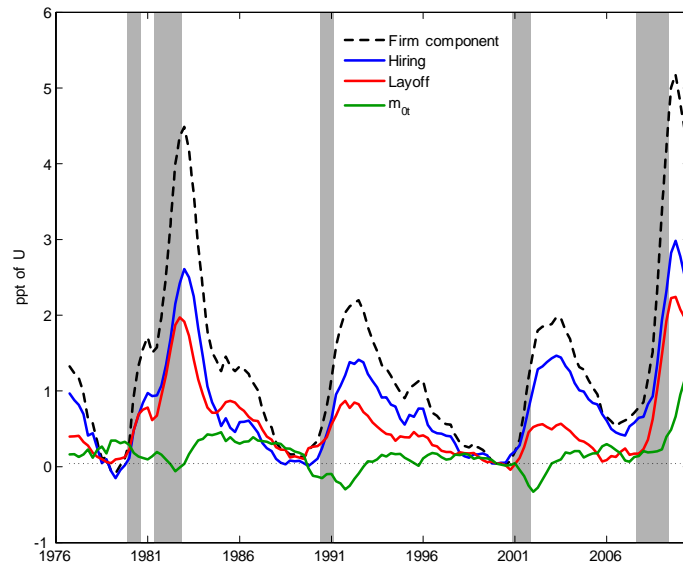
Figure 6: The firm components of unemployment: hiring, layoff and changes in matching efficiency. The dashed line is the sum of all three components. 4-quarter moving averages, 1976-2010. The series are normalized to zero in 2000Q3.
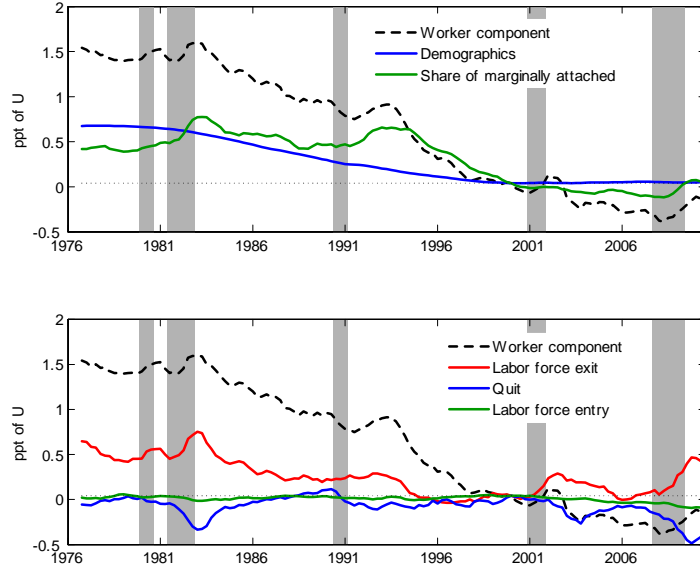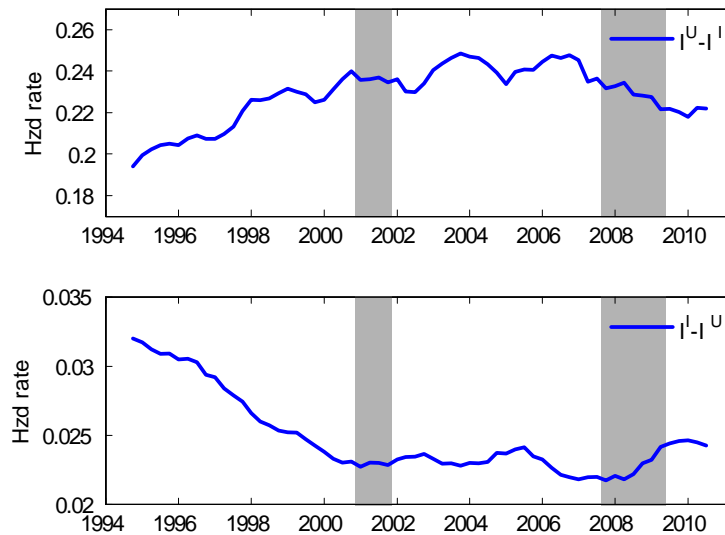
Figure 7: The worker components of unemployment: demographics, fraction of marginally attached, quit, labor force entry/exit. The dashed line is the sum of all components. 4-quarter moving averages, 1976-2010. The series are normalized to zero in 2000Q3.

Figure 8: The $I^U - I^I$ transition rate (upper-panel) and the $I^I - I^U$ transition rate (lower panel). 4-quarter moving averages, 1994-2011.
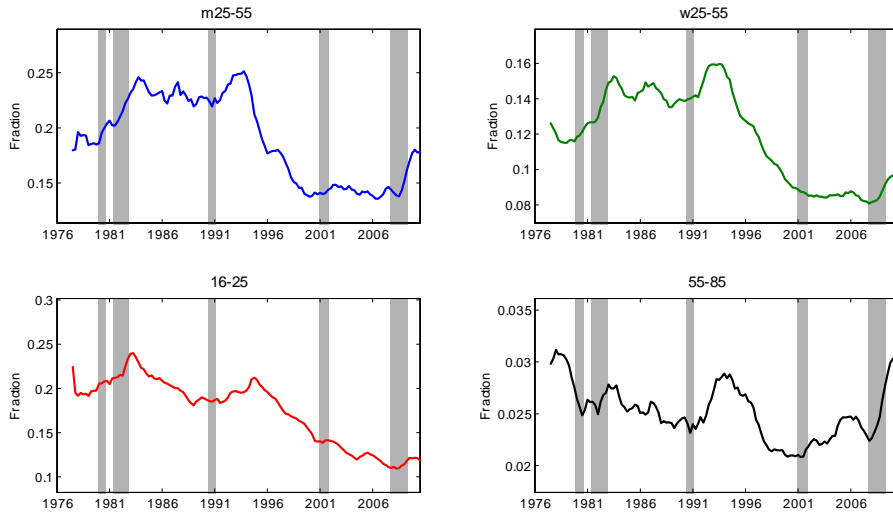
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Figure 9: Fraction of marginally attached in the inactivity pool by demographic group: male 25-55, female 25-55, younger than 25, and older than 55, 1976-2010. 4-quarter moving averages, 1976-2010.
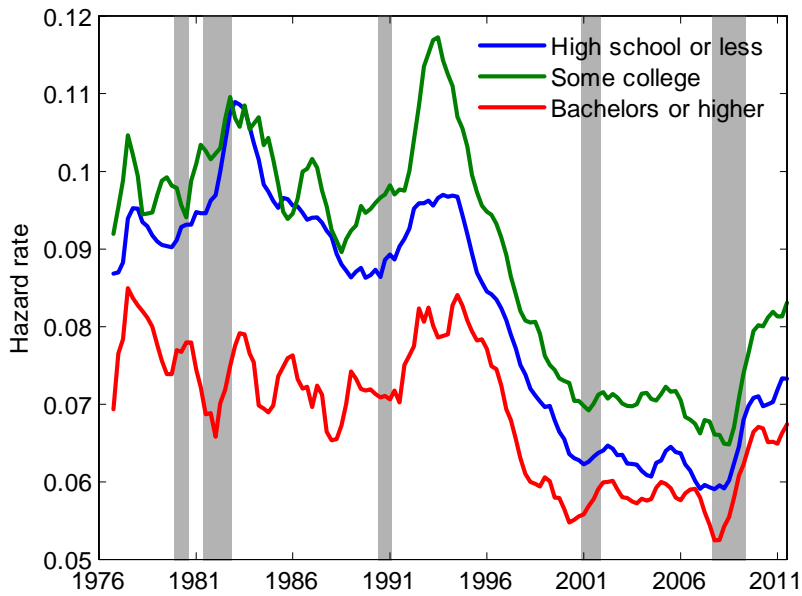
Figure 10: Fraction of marginally attached in the inactivity pool by education group: High school or less, Some college or associated degree, Bachelors or higher, 1976-2010. 4-quarter moving averages, 1976-2010.
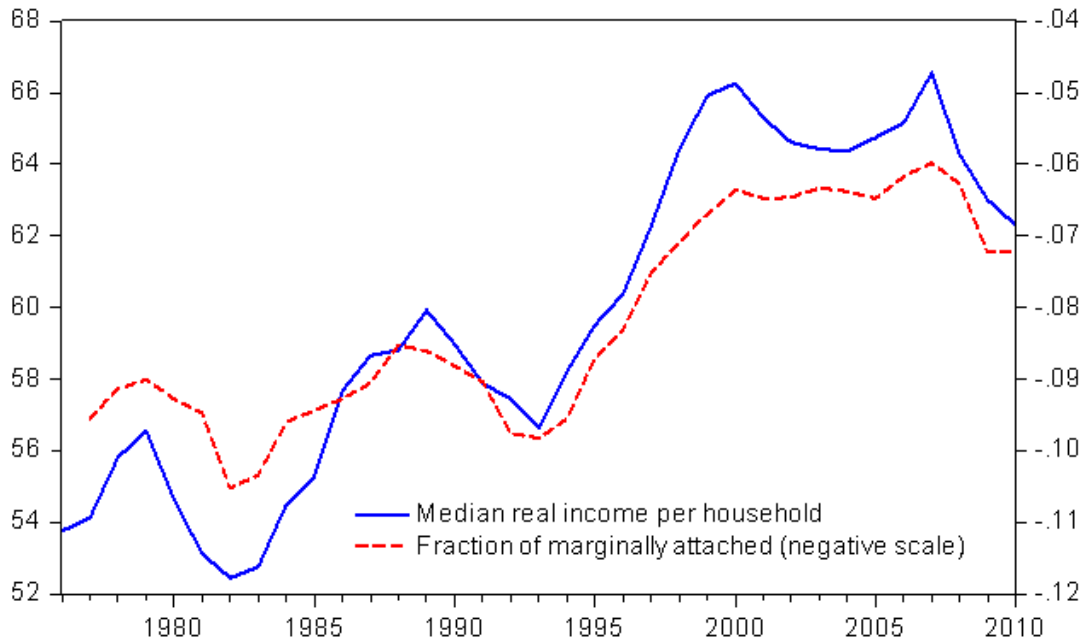
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Figure 11: Median real income per household (in thousands of 2010 US$) and fraction of marginally attached in the inactivity pool (reversed scale), 1976-2010.
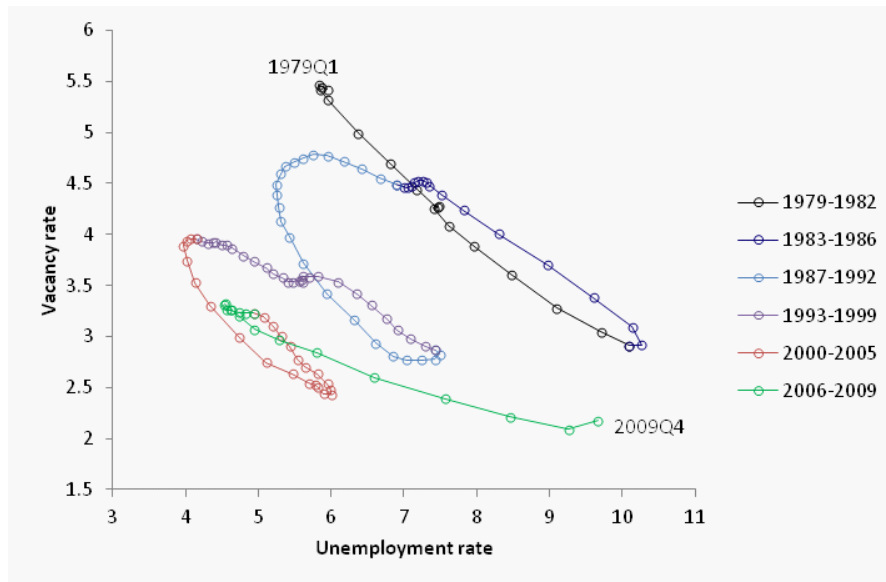

Figure 12: The US Beveridge curve, 1979Q1-2009Q4. For clarity of exposition, we plot the 4-quarter moving averages of the unemployment and vacancy rates.
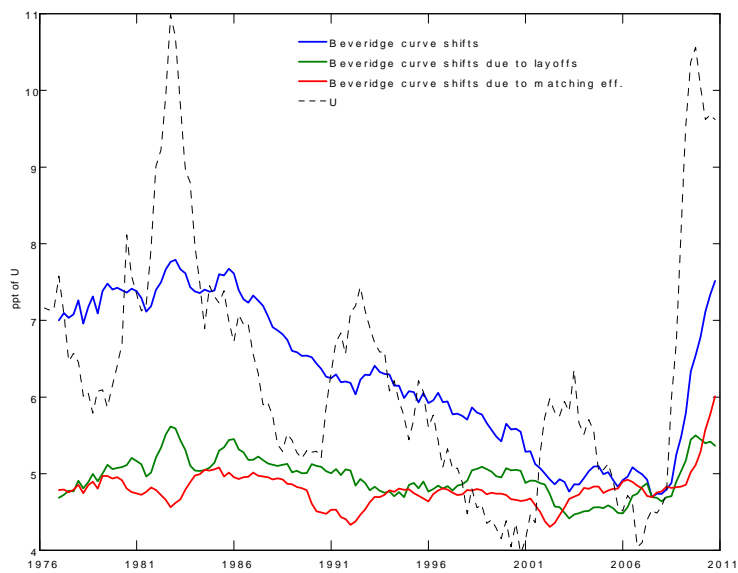
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Figure 13: Total Beveridge curve shifts (blue line) and Beveridge curve shifts due to layoffs (green line). The dashed line represents stead-state unemployment. 1976-2010.

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Table 1: Estimation

Dependent variable:	λ^{UE}	λ^{UE}	$\lambda^{IE|\text{I-LF}}$
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)	--
$a_0 (\lambda^{UE})$	--	--	0.28*** (0.02)
$a_0 (I^U/I)$	--	--	-0.12*** (0.01)
$a_0 (\lambda^{UI})$	--	--	0.13*** (0.03)
R^2	0.85	--	0.86

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 component	Hiring	0.37	0.03	0.56
	Layoffs	0.33	0.11	0.36
	Quits	-0.06	0.01	-0.07
	LF exit	0.11	0.17	0.10
	LF entry	0.00	0.02	0.00
Worker component	I^U/U { $\lambda^{I^I I^U}$: 73% $\lambda^{I^U I^I}$: 33% }	0.07	0.20	0.05
	Demographics	0.07	0.41	0.00
	Other	0.02	0.04	-0.01
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 contribution from movements in $\lambda^{II\text{-}IU}$ and from movements in $\lambda^{IU\text{-}II}$ over 1994-2010.