On the Importance of the Participation Margin for Labor Market Fluctuations*

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Abstract

Conventional analyses of labor market fluctuations ascribe a minor role to labor force participation. By contrast, flows-based analyses suggest the participation margin accounts for around one-third of unemployment fluctuations. A novel stock-flow apparatus carefully establishes these facts, delivering three further contributions. First, the role of the participation margin appears robust to adjustments for spurious transitions induced by reporting error. Second, conventional stocks-based analyses are subject to a stock-flow fallacy, neglecting offsetting forces of worker flows on the participation rate. Third, recessionary increases in labor force attachment among the unemployed are a leading explanation for the role of the participation margin.

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1 Introduction

What is the role of the labor force participation margin in shaping fluctuations in the unemployment rate? The majority of modern research has operated under the assumption that movements of individuals in and out of the labor force play only a minor role in unemployment fluctuations. From an empirical perspective, while there are clear, opposite cyclical patterns in rates of employment and unemployment, the labor force participation rate displays only a modest cyclicality in the United States (see, for example, Figure 1). Mirroring this, recent theoretical models of labor market fluctuations, such as those informed by the search and matching tradition of Mortensen and Pissarides (1994), typically proceed under a two-state abstraction, focusing on the margin between employment and unemployment.[1]

In this paper we take a closer look at the role of the participation margin in the evolution of unemployment over the business cycle. Our analysis yields a rich set of empirical findings that challenge the conventional practice of abstracting from this margin. First, standard estimates of worker flows among the three labor market states reveal that the moderate cyclicality of the stock of labor force participants masks substantial cyclicality in worker flows between unemployment and nonparticipation. Second, we find this channel to be quantitatively significant: we estimate that transitions at the participation margin account for around one-third of the cyclical variation in the unemployment rate. Third, the latter result is robust to conventional and practical adjustments of data for spurious transitions, and for time aggregation. Fourth, we instead show that inferences from conventional, stocks-based analyses of labor force participation are subject to a stock-flow fallacy, neglecting the offsetting forces of worker flows that underlie the modest cyclicality of the participation rate. Finally, new estimates of heterogeneity in worker flows across labor market histories reveal that an important part of the contribution of the participation margin, and therefore of unemployment fluctuations in general, can be traced to a novel channel based on cyclical shifts in the composition of labor market attachment among the unemployed.

The starting point for our analysis is the standard data source for worker flows in the United States: the longitudinally-linked monthly Current Population Survey (CPS) mi-

[1] Theoretical papers that adopt a two-state abstraction are too numerous to cite. Exceptions to this tendency include: Alvarez and Veracierto (1999); Andolfatto and Gomme (1996); Andolfatto, Gomme, and Storer (1998); Campolmi and Gnocchi (2014); Garibaldi and Wasmer (2005); Kim (2001); Krusell, Mukoyama, Rogerson and Şahin (2010a, 2010b, 2012); Pries and Rogerson (2009); Shimer (2013); Veracierto (2008). Recent empirical research on labor market flows also emphasizes the roles of job loss and job finding over that of the participation margin. See, for example, Braun, De Bock, and DiCecio (2006); Elsby, Michaels, and Solon (2009); Fujita and Ramey (2009); Hall (2005a,b); and Shimer (2012).

crodata, known as the "gross flows."[2] In section 2 we update these estimates and review their basic cyclical properties. There we confirm the countercyclicality of the employment-to-unemployment transition probability, and the procyclicality of the unemployment-to-employment transition probability, that have been widely documented in previous literature. But, we also highlight an often-neglected feature of the gross flows that are crucial to our findings: During recessions, unemployed workers are less likely to flow out of the labor force, and nonparticipants are more likely to flow into unemployment. Both forces will contribute to the rise in the level of unemployment that accompanies recessions. The remainder of this paper investigates the robustness of this observation, provides an accounting framework that allows one to quantify its magnitude, and explores potential explanations.

We first consider robustness. A particular concern is that gross flows data are susceptible to classification errors in recorded labor market status (National Commission on Employment and Unemployment Statistics, 1979). While such errors may largely cancel in measured labor market stocks, they can accumulate in estimates of worker flows, inducing spurious measured transitions. Prior research has found these errors to be substantial, especially for transitions between unemployment and nonparticipation (Abowd and Zellner, 1985; Poterba and Summers, 1986; and Chua and Fuller, 1987). It is natural to worry, then, that such measurement errors might be responsible for the cyclical behavior of participation flows.

In section 3, we take this possibility seriously by exploring alternative adjustments for misclassification. We consider two approaches. First, following Blanchard and Diamond (1990), we adjust the gross flows data using Abowd and Zellner's (1985) estimates of misclassification probabilities based on resolved labor force status in CPS reinterview surveys. Since these estimates are inferred under a particular assumption about the nature of classification errors, however, we also examine a second, more practical adjustment of the data: We recode sequences of recorded labor market states to eliminate high-frequency reversals of transitions between unemployment and nonparticipation. One example of the latter are consecutive monthly transitions from nonparticipation to unemployment and then back to nonparticipation again. Since our method involves "ironing out"such NUN sequences, we sometimes will refer to these adjusted flows as "*deNUNified*" flows, but the approach also recodes UNU sequences analogously.

As foreshadowed in prior literature, these adjustments substantially reduce estimated flows that involve transitions in and out of the labor force. However, the adjusted flows under

[2]Early analyses of these data include Kaitz (1970), Marston (1976), Perry (1972). More recent analyses include Blanchard and Diamond (1990), Fujita and Ramey (2006), and Shimer (2012).

both the more practical recoding approach and the Abowd and Zellner (1985) adjustment line up closely, despite their being based on different motivations, and paint a consistent picture of the cyclicality of worker flows at the participation margin: While the countercyclicality of the nonparticipation-to-unemployment rate is diminished somewhat by both conventional and practical adjustments for classification error, the procyclicality of the rate of outflow of unemployed workers to nonparticipation appears to be a robust feature of the dynamics of the U.S. labor market.[3] This picture is reaffirmed in section 4, which further adjusts worker flows for time aggregation bias associated with multiple transitions that are missed between the discrete, monthly surveys implemented in the CPS.

Given the apparent robustness of this result, we then turn to consider its quantitative magnitude in accounting for labor market fluctuations. In section 5 we devise a novel accounting framework that allows one to decompose the time-series variation in each of the labor market stocks into components accounted for by each of the associated worker flow hazards.[4] Application of this decomposition informs three results: First, the participation margin accounts for a substantial fraction—around one-third—of the rise in U.S. unemployment during recessions. Second, and crucially, this result holds even after adjustments for classification error. Third, the majority of the contribution of the participation margin is accounted for by the procyclicality of the flow rate from unemployment to nonparticipation.

As discussed in the opening paragraphs of this paper, these findings challenge conventional wisdom that modest reductions in labor force participation during recessions in fact serve to *reduce* slightly rises in unemployment. In section 6, we explain why such reasoning is an example of a stock-flow fallacy. Like unemployment, the cyclical behavior of labor force participation is itself the outcome of subtle interactions of movements in worker flow rates. We show that much of the variation in labor force participation can be traced to movements in flows between *employment* and nonparticipation. Such flows have only an indirect effect on the unemployment rate, yet an analysis of labor market stocks would incorrectly ascribe

[3]We also offer an explanation for why the countercyclicality of the N-to-U rate is shaded down in the adjusted data. Classification errors can impart a countercyclical bias in estimates of the number of workers transitioning between U and N because recessions are accompanied by a rise in the number of nonemployed individuals *at risk* of being misclassified.

[4]Our approach makes several methodological contributions. It accounts for the nonlinear relationship between flows and stocks, as well as the out-of-steady-state transmission of past movements in worker flows (in contrast to Shimer, 2012; Gomes, 2012; King, 2011; Kudlyak and Schwartzman, 2012). It infers variance contributions for *each* of the underlying worker flows, rather than for combinations of participation flows (as in Petrongolo and Pissarides, 2008; Barnichon and Figura, 2012; Elsby, Smith and Wadsworth, 2011; Smith, 2011). Finally, it can estimate flow contributions to any combination of labor market stocks, such as the participation rate, providing a key insight into the stock-flow fallacy we note in section 6.

to this variation an unemployment-reducing role in times of recession.

A complete understanding of U.S. unemployment fluctuations thus requires an understanding of the apparent cyclical movements in worker flows at the participation margin. In section 7, we explore a set of potential explanations toward that end. Although accounts for the countercyclicality of labor force entry—for example, based on classification errors or the added-worker effect—receive limited empirical support,[5] we identify one particularly fruitful account for the procyclical behavior of the rate of labor force exit from unemployment. Using gender, age and past labor force status as proxies for labor market attachment, we find that prime-aged, male unemployed individuals who were employed in the past are much less likely to exit the labor force than their counterparts. Consistent with the wave of job loss that occurs at the onset of downturns, the composition of the unemployment pool shifts during recessions *towards* such attached workers. We find that this compositional shift along these few dimensions accounts for a large part—around three-quarters—of the recessionary decline in the rate of exit of unemployed workers from the labor force.[6] Since the latter accounts for the majority of the contribution of the participation margin, this is an important result.

In closing, we reflect on the implications of our results for future research. Our findings emphasize the interaction of labor supply with unemployment determination as a means to understanding labor market fluctuations. But the important role of labor market attachment that we uncover also informs the nature of the economics behind this interaction—in particular, the role of worker heterogeneity, and the salience of marginal individuals that arises naturally in such an environment. These results caution against the view that the presence of such marginally-attached individuals undermines the economic significance of cyclical movements in the unemployment rate. To the contrary, we find that the degree of labor market attachment in the jobless pool *rises* systematically during downturns. Our results therefore underscore the particular importance of unemployment in times of recession.

[5] Adjustments for misclassification reduce the estimated countercyclicality of labor force entry somewhat, but the magnitude depends on the particular adjustment. Likewise, the countercyclicality of labor force entry is not dominated by prime-aged women—the group typically associated with the added worker effect—but rather is broad-based by age and gender.

[6] Baker (1992) and Shimer (2012) investigate the role of compositional shifts on the *total* rate of outflow from unemployment, finding small effects. The difference with our result is twofold: First, we further adjust for composition over past labor market status, a dimension we find to be important. Second, we focus on the outflow rate *to nonparticipation*. Interestingly, we find offsetting effects on outflows *to employment*, consistent with Baker's and Shimer's analysis of total outflows, and with our finding that the composition of the unemployment pool shifts in recessions towards more attached workers.

2 Data on labor market flows

The data we use are the "gross flows" data from the Current Population Survey (CPS). These measures of worker flows are obtained by exploiting a rotating-panel element in the CPS sample design. Addresses selected into the survey remain in the sample for four consecutive months, rotate out for eight months, and then rotate back in again for a further four months. A consequence is that, in any given month, the CPS is comprised of eight "rotation groups," six of which will be surveyed again in the subsequent month. In principle, then, a maximum of three-quarters of the sample in a given month can be linked longitudinally to their responses one month later. In practice, however, it is possible to match approximately two-thirds of the sample across consecutive months due to non-response, changes of residence and so on.

Using these longitudinally-linked microdata, it is straightforward to estimate worker flows and their associated transition probabilities. For example, the probability that an unemployed worker finds a job and is employed one month later can be computed simply as the fraction of the unemployed in a given month who subsequently report that they are employed in the next month's survey. Using this method, one can compute monthly flow transition probabilities among employment, unemployment and nonparticipation for each month of available data.

Measures of worker flows based on this approach have been made available from a number of sources. Data for February 1990 onwards are posted on the Bureau of Labor Statistics website. Shimer (2012) has computed analogous measures using CPS microdata from January 1976. Data from June 1967 to December 1975 have been tabulated by Joe Ritter and made available by Hoyt Bleakley.

These measures have become the standard source for estimating worker flows among labor force states. They are the basis of a long line of research on unemployment flows, and have informed much of what we know about labor market dynamics (see, among many others, Kaitz, 1970; Perry, 1972; Marston, 1976; Blanchard and Diamond, 1990; Fujita and Ramey, 2006; and Shimer, 2012). While these data are known to be subject to a number of drawbacks that are the subjects of the ensuing sections, it is instructive first to summarize the basic cyclical properties of worker flows in the gross flows data. The "unadjusted" series in Figure 2 plot the raw gross flows transition probabilities between employment, unemployment and nonparticipation. There are clear, systematic empirical regularities in the behavior of these measures over the business cycle. Among these, a particularly well-emphasized observation is the notable countercyclicality of the employment-

to-unemployment probability, and the prominent procyclicality of the unemployment-to-employment probability, a feature confirmed in panels (a) and (b) of Figure 2. Clearly, both of these contribute to the cyclicality of the unemployment rate.

Considerably less emphasis has been given to fluctuations in flow probabilities between unemployment and nonparticipation over the business cycle, however. Panels (c) and (d) of Figure 2 reveal that rates of inflow to unemployment from nonparticipation rise substantially in recessions, while rates of outflow to nonparticipation decline substantially. By the same token, these flows in and out of the labor force also must contribute to the rise in unemployment that accompanies recessions in the United States. The robustness, magnitude, and reasons for this contribution are the focus of the remainder of the paper.

3 Adjustments for classification error

A drawback of the gross flows estimates is that they are sensitive to *classification errors* in recorded labor market states, which may lead to spurious measured transitions. For example, imagine a respondent who is in fact unemployed for three consecutive surveys, but who is misclassified as out of the labor force in the second survey. In this example, we would observe two spurious measured transitions—from unemployment to nonparticipation and vice versa. Estimates of classification errors suggest that spurious transitions are particularly important for such transitions between unemployment and nonparticipation (Abowd and Zellner, 1985; Poterba and Summers, 1986).

Because these transitions between unemployment and nonparticipation are the particular focus of our study, we take the potential effects of such classification errors seriously. In order to consider whether our results are affected by these errors, we examine the effect of two specific adjustments of the data. In the remainder of this section we introduce these two adjustment methods and document their effects on the time series behavior of labor market stocks and flows.

3.1 Abowd and Zellner (1985) correction

The first adjustment we consider is based on a literature that has sought to estimate the magnitude of classification errors in recorded labor market status using data from a subsample of the CPS (around one-thirtieth of the overall sample) that is reinterviewed each month (see, for example, Abowd and Zellner, 1985; Poterba and Summers, 1986; and Chua and

Fuller, 1987). Denoting the measured stocks of employed, unemployed and nonparticipants respectively as $\widehat{E}$, $\widehat{U}$, and $\widehat{N}$, these studies assume the following relation between measured stocks and their "true" counterparts E, U, and N:

$$\begin{bmatrix} \widehat{E} \\ \widehat{U} \\ \widehat{N} \end{bmatrix}_t = \underbrace{\begin{bmatrix} 1-\varepsilon_{EU}-\varepsilon_{EN} & \varepsilon_{UE} & \varepsilon_{NE} \\ \varepsilon_{EU} & 1-\varepsilon_{UE}-\varepsilon_{UN} & \varepsilon_{NU} \\ \varepsilon_{EN} & \varepsilon_{UN} & 1-\varepsilon_{NE}-\varepsilon_{NE} \end{bmatrix}}_{\mathbf{E}} \begin{bmatrix} E \\ U \\ N \end{bmatrix}_t, \tag{1}$$

where ε_{ij} is the probability that an individual with true labor market state i is recorded as measured state j.

Estimates of the elements of the matrix of classification error probabilities $\mathbf{E}$ are based on a series of CPS reinterview surveys in which CPS respondents were contacted for a follow-up interview to check the validity of their original responses. Table 1 reproduces the estimate of $\mathbf{E}$ from Abowd and Zellner (1985, Table 6). It can be seen that the most common classification error relates to individuals counted as nonparticipants whose "resolved" status is unemployed. This is true for approximately 10 percent of persons who were determined to be unemployed upon reinterview.

These estimates of $\mathbf{E}$ allow one to infer estimates of the underlying corrected worker flows from the raw measured gross flows. Specifically, if we denote the *number* (as opposed to the transition rate) of individuals flowing from state i in month $t-1$ to state j in month t by ij_t, and the associated matrix of these flows by

$$\mathbf{N}_t = \begin{bmatrix} EE & UE & NE \\ EU & UU & NU \\ EN & UN & NN \end{bmatrix}_t, \tag{2}$$

then Poterba and Summers (1986) show that measured flows, $\widehat{\mathbf{N}}_t$, can be related to their true counterparts $\mathbf{N}_t$ according to the relation $\widehat{\mathbf{N}}_t = \mathbf{E}\mathbf{N}_t\mathbf{E}'$. One may then infer the matrix of corrected flows simply by inverting this relation to obtain

$$\mathbf{N}_t = \mathbf{E}^{-1}\widehat{\mathbf{N}}_t\left(\mathbf{E}^{-1}\right)'. \tag{3}$$

An implicit assumption that underlies this adjustment is that classification errors are time-invariant. *A priori*, then, it would seem unlikely that such misclassification could

Table 1: Abowd and Zellner (1985) estimates of classification errors (%)

Original interview status	Status determined on reinterview: Employed	Unemployed	Non-participant
Employed	98.78	1.91	0.50
Unemployed	0.18	88.57	0.29
Non-participant	1.03	9.52	99.21

Source: Abowd and Zellner (1985, Table 6).

explain the *cyclical* fluctuations in these flows we document above. We argue that such a conclusion would be premature. To see why, it is helpful to consider a simple special case in which classification errors exist only between unemployment and nonparticipation—that is, $\varepsilon_{ij} = 0$ for all $ij \notin \{UN, NU\}$. For small ε_{UN} and ε_{NU}, we show in the Appendix that measured flows between unemployment and nonparticipation can be related to error-free flows according to the simple approximations:

$$\begin{aligned} \widehat{UN}_t &\approx (1 - \varepsilon_{UN} - \varepsilon_{NU})\, UN_t + \varepsilon_{UN} UU_t + \varepsilon_{NU} NN_t, \text{ and} \\ \widehat{NU}_t &\approx (1 - \varepsilon_{UN} - \varepsilon_{NU})\, NU_t + \varepsilon_{UN} UU_t + \varepsilon_{NU} NN_t. \end{aligned} \tag{4}$$

The first terms in these expressions capture respectively the fraction of true flows that show up in measured transitions. The subsequent terms capture spurious transitions driven by classification errors.

Equation (4) highlights why even time-invariant classification errors can imply a bias in measured flows that varies over the cycle. The key is that the number of individuals who remain unemployed UU_t rises substantially in recessions as the stock of unemployed workers itself rises. As a result, this imparts a countercyclical bias in measured transitions between unemployment and nonparticipation, UN_t and NU_t. The intuition is simple: During a recession, there are more nonemployed individuals *at risk* of being misclassified.

3.2 Recoding of unemployment-nonparticipation cyclers

The Abowd-Zellner correction for classification errors has two potential shortcomings. First of all, it is based on data from past reinterview surveys.[7] Second, it relies on a maintained assumption that measurement errors are time-invariant.[8] We therefore examine an alternative adjustment of measured transitions which, for reasons that will become clear, we sometimes will refer to as *deNUNified* flows. This adjustment takes a more practical approach: It identifies individuals whose measured labor market state cycles back and forth between unemployment and nonparticipation from month to month, and assesses the effect of omitting such transitions on the cyclical properties of the associated flows.

We first isolate sequences of transitions that involve the reversal of a transition from unemployment to nonparticipation, and *vice versa*. We denote a sequence of transitions from unemployment to nonparticipation to unemployment as UNUs, and analogously N-to-U-to-N sequences as NUNs. We then examine the effects of recoding the data to eliminate these transition reversals—hence "deNUNified" flows—although we also recode UNU sequences symmetrically. Table 2 summarizes the flow sequences that are recoded in this way.

Approaches of this kind recently have been used as a common robustness check in studies of worker flows (see Rothstein 2011, and Farber and Valletta 2013). It is important to note, however, that the goal of the exercise is not to provide a definitive correction of labor market flows for classification errors. By treating all transition reversals between unemployment and nonparticipation as measurement error the approach inevitably will miss some spurious transitions between unemployment and nonparticipation, and will purge some genuine transitions. Rather, the method is intended more as a stress test. The approach complements the adjustment in the previous subsection in the sense that it relies neither on the use of reinterview data from the past nor on an assumption of time-invariant classification errors.

The motivation for this robustness check is based on the following considerations. First, we find that (unadjusted) transitions between unemployment and nonparticipation appear to play an important role in unemployment dynamics. Second, evidence from reinterview surveys (as in Table 1) suggests reporting errors between U and N are particularly signif-

[7] Unfortunately, CPS reinterview survey data are no longer being released by the BLS. It is therefore not possible to update the estimates of **E** in Table 1.

[8] That said, Abowd and Zellner (1985) do present adjusted estimates of worker flows based on estimates of classification error probabilities computed at a quarterly frequency for the years 1977 to 1982 (see their Figures 1 through 5 and the surrounding discussion). They suggest that there is little evidence of time variation in the magnitude of adjustment, suggesting that their classification error estimates do not vary much over their sample period.

Table 2: Recoding of unemployment-nonparticipation cyclers: "deNUNified" flows

	Measured	Recoded
NUNs	$NNUN$	$NNNN$
	$NUNN$	$NNNN$
	$ENUN$	$ENNN$
	$NUNE$	$NNNE$
	$.NUN$	$.NNN$
	$NUN.$	$NNN.$
UNUs	$UUNU$	$UUUU$
	$UNUU$	$UUUU$
	$EUNU$	$EUUU$
	$UNUE$	$UUUE$
	$.UNU$	$.UUU$
	$UNU.$	$UUU.$
Unadjusted	$NUNU$	$NUNU$
	$UNUN$	$UNUN$

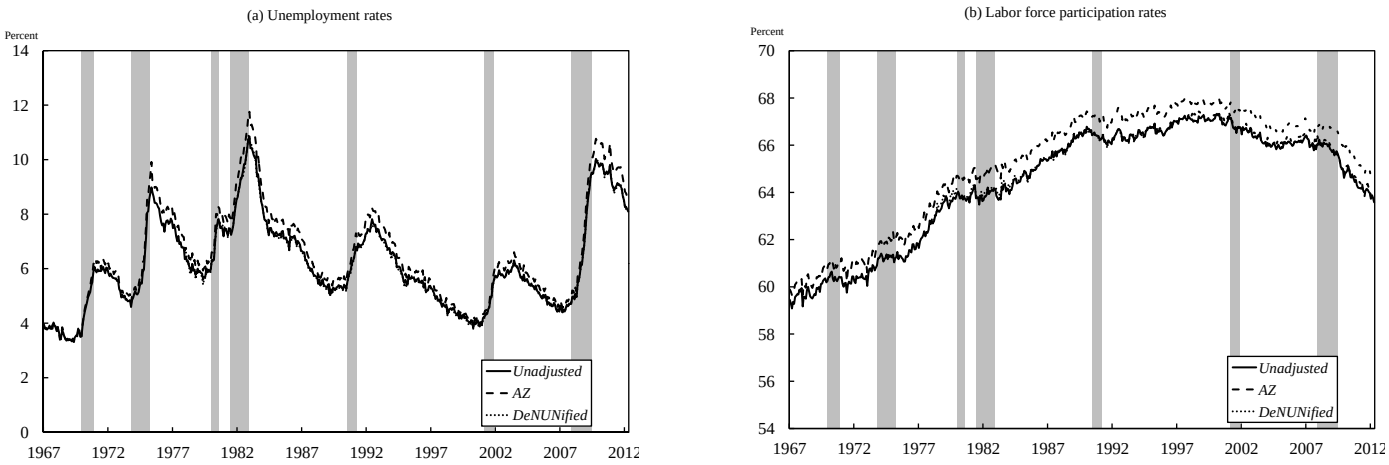
Note: The notation ABCD refers to a sequence of transitions associated with up to four consecutive monthly individual labor market states (that is, from A to B to C to D). A "." is used to denote missing observations.

icant. This is also intuitive, as the requirement for being classified as unemployed—that a nonemployed individual has "looked for work" in the four weeks prior to the survey—is fundamentally fuzzy. Thus, it makes sense to investigate whether these two observations might be related. We do this by checking whether the cyclicality of worker flows between U and N is significantly altered by "ironing out" reversals of transitions between those two states.

Beyond its intuitive appeal, there are further reasons to suspect that such transition reversals are likely to be spurious. For example, if observed UNU transitions were real, respondents also would report unemployment durations of (less than) one month in the third month of the sequence. As noted by Elsby et al. (2011) and Farber and Valletta (2013), however, such respondents often report durations well in excess of one month. Second, and relatedly, Rothstein (2011) notes that eliminating such transition reversals closes the gap between unemployment survival functions estimated from longitudinally-linked and cross-sectional CPS data.[9]

[9]Thanks to a comment from the Editor, we also investigated the potential role of discouragement in UNU and NUN transitions. Since 1994, the CPS has implemented a consistent measure of discouragement,

Figure 1: Unemployment and labor force participation rates: unadjusted and adjusted for spurious transitions



To identify, and therefore purge, these transition reversals, it is necessary to match an individual's labor market status across more than just two months. As noted in section 2, the rotation structure of the CPS is such that each household is surveyed for two sets of four consecutive months, with an intervening eight-month hiatus. Thus, the CPS allows one to identify an individual's labor market status for a maximum of four successive months. These are the data that we use for our recoding procedure.

3.3 Stocks and flows adjusted for classification error

Figure 1 plots the published unemployment and participation rates together with those implied by the Abowd and Zellner (1985, AZ) correction and the deNUNified flows. The left and right panels respectively depict the time series for the associated unemployment rates and labor force participation rates.

We find that both adjustments for classification errors imply quite small adjustments of labor market stocks. The reason relates to the intuition that classification errors will tend to cancel out in the cross section (see, for example, National Commission on Employment and

defined as those out of the labor force who want and are available for work, have searched in the prior 12 months, but have not searched in the prior 4 weeks because they believed no jobs were available for them. Denoting this state by D, we found that only 11.9 percent of UNU transitions were UDUs, and only 1.2 percent of NUNs were DUDs, between 1994 and 2012. Thus, conventional measures of discouragement do not account for the high frequency transitions between unemployment and nonparticipation.

Unemployment Statistics, 1979). In accordance with this intuition, we find that the number of NUNs and UNUs tend almost to offset one another, so that our recoding procedure leaves the implied stocks almost unchanged. The AZ correction induces a modest adjustment to the levels of the unemployment and participation rates. This arises because the most common error is the misclassification of someone who is unemployed as being out of the labor force (see Table 1). As a result, the correction reclassifies a number of people from nonparticipation into unemployment, thus raising slightly both the unemployment rate and the participation rate. In addition, Figure 1 suggests that both adjustments have a very small effect on the cyclicality of labor market stocks.[10]

In contrast, we find that estimated worker flows are more sensitive to the presence of classification errors, consistent with the intuition above. The effects of each adjustment for classification error on estimated worker flows are illustrated in Figure 2. This plots the estimated transition probabilities $p_{ij_t} \equiv ij_t/i_{t-1}$ for $i, j \in \{E, U, N\}$, that have been adjusted for classification errors, together with their unadjusted counterparts for reference. The AZ-adjusted flows are obtained by applying the adjustment in equation (3) to the gross flows data described above in Section 2. The deNUNified flows instead are based on CPS microdata in which individuals' outcomes have been matched over all months in sample.

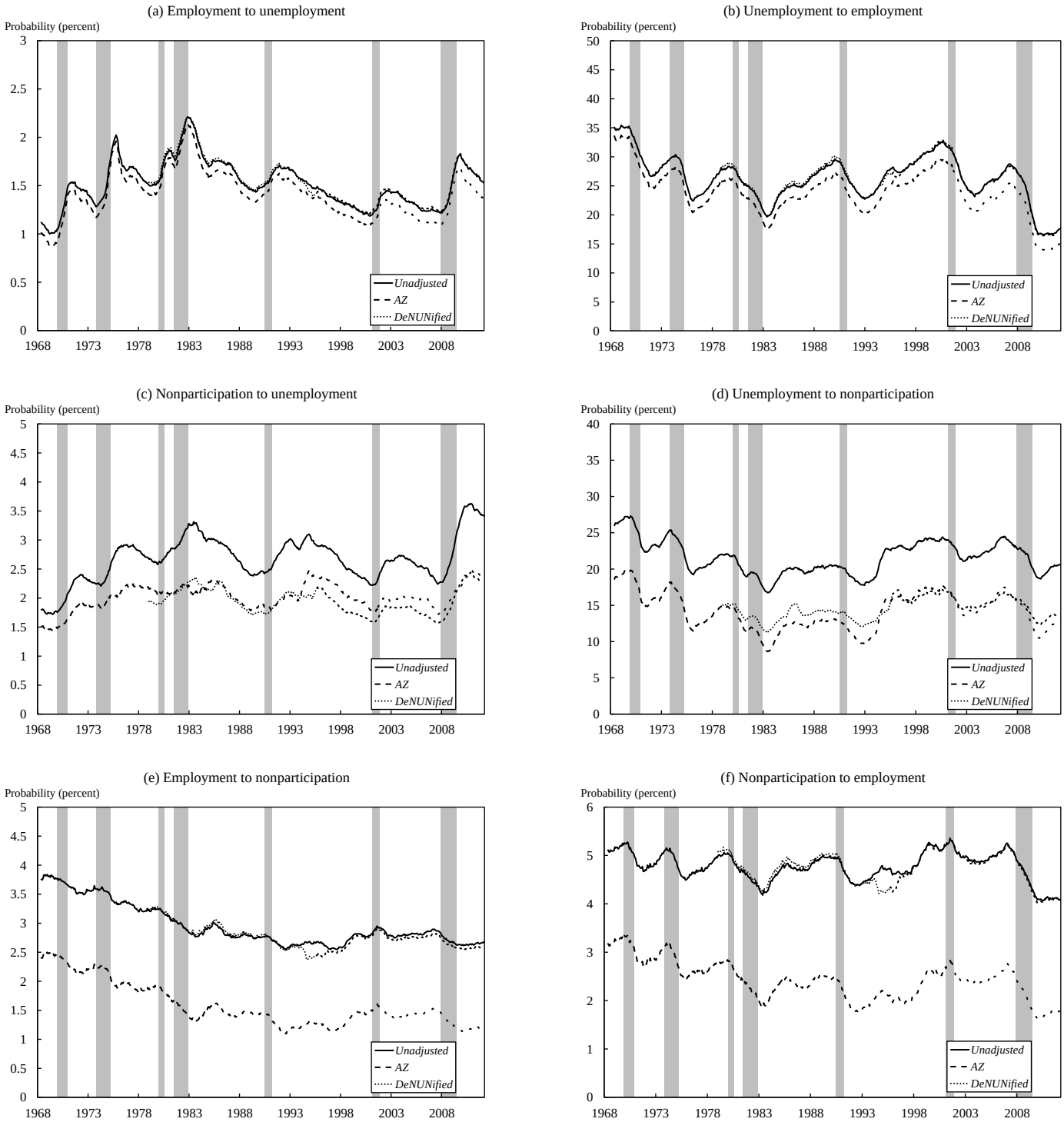
In keeping with prior literature, for all plotted series we implement a correction for *margin error* that restricts the estimates of worker flows to be consistent with the evolution of the corresponding labor market stocks depicted in Figure 1.[11] Our approach is similar to that employed by Poterba and Summers (1986), and solves for the set of stock-consistent transition probabilities that minimizes the weighted sum of squares of the margin-error adjustments, and is described in detail in the Appendix. In practice, however, we find that the margin-error adjustment has a very small effect on the estimated transition probabilities.

Consistent with the notion that classification errors can accumulate in estimated flows leading to spurious estimated transitions, Figure 2 reveals that the adjusted flows lie systematically below their unadjusted counterparts. As noted in prior literature, flows in and

[10] Recent work by Feng and Hu (2012) applies a different classification error adjustment that implies larger increases in the unemployment rate and a smaller rise in the participation rate. The directions of the adjustments are similar, however.

[11] Margin error can arise for a number of reasons. First, we ignore movements in and out of the working-age population, such as those who turn 16, die, immigrate, emigrate and so on, that are classified as "other" in the BLS gross flows data. In addition, it is possible that attrition of households from our matched CPS samples is not random with respect to labor force status. For both these reasons, implied changes in labor market stocks in our matched samples may not necessarily replicate changes in the published stocks. Our finding, however, is that there is only a small discrepancy between implied and published changes in stocks.

Figure 2: Monthly flow transition probabilities corrected for margin error: unadjusted and adjusted for spurious transitions



out of the labor force particularly are affected. Transition rates between employment and nonparticipation are approximately halved, while those between unemployment and nonparticipation are adjusted down by around one third.

Interestingly, the cyclicality of rates of transition between U and N also appears to be affected in a manner consistent with the intuition of equation (4). While the nonparticipation-to-unemployment transition rate remains countercyclical, its fluctuations are seen to be less volatile than in the raw gross flows data. In contrast, the adjusted unemployment-to-nonparticipation rate retains its procyclicality. Both of these observations dovetail with the logic above that classification errors can lead to a countercyclical bias in flows between unemployment and nonparticipation.

Figure 2 also illustrates the impact of the adjustment for classification error based on the recoding of unemployment-nonparticipation cyclers. Unsurprisingly, the adjustment has little effect on flow transition rates between employment and unemployment, and employment and nonparticipation. The time series for these flow hazards differ slightly from those implied by the raw gross flows because the adjusted flows are based on the smaller sample of households that can be matched across four consecutive months (rather than just two).

A striking aspect of Figure 2, however, is that the deNUNified transition rates between unemployment and nonparticipation correspond very closely to the adjusted flows based on the Abowd and Zellner (1985) estimates of time-invariant classification errors. Note that there is no mechanical reason to expect this: The AZ adjustment is based on error probabilities implied by resolved labor force status from reinterview data; the recoding approach simply unwinds reversals of transitions between unemployment and nonparticipation. The correspondence between the two adjustments holds both in terms of the levels of these flow hazards, as well as their cyclicality. Both the rates of inflow to and outflow from unemployment on the participation margin are reduced by around one-third. As in the AZ-adjusted data, inflows into unemployment from out of the labor force are weakly countercyclical. Importantly, the rate at which the unemployed flow out of the labor force continues to fall substantially in times of recession.

4 Adjustments for temporal aggregation

Due to the monthly frequency of the CPS data, the gross flows provide us only with a series of snapshots of an individual's labor force status observed at discrete points in time. In practice, however, a person may make multiple transitions between consecutive surveys. For

this reason, the gross flows estimates will not provide an accurate picture of the underlying flows—they will miss some transitions and incorrectly include others.

To see this, imagine an individual who is recorded as a nonparticipant in one month and as employed in the next month. In principle, there is an infinity of possible (though not equally-probable) paths that would yield this observation in discrete-time data. For example, the person could have flowed from nonparticipation to unemployment, and then from unemployment to employment. Discrete-time data would miss the latter two transitions, and would incorrectly ascribe them to a single employment to nonparticipation flow.

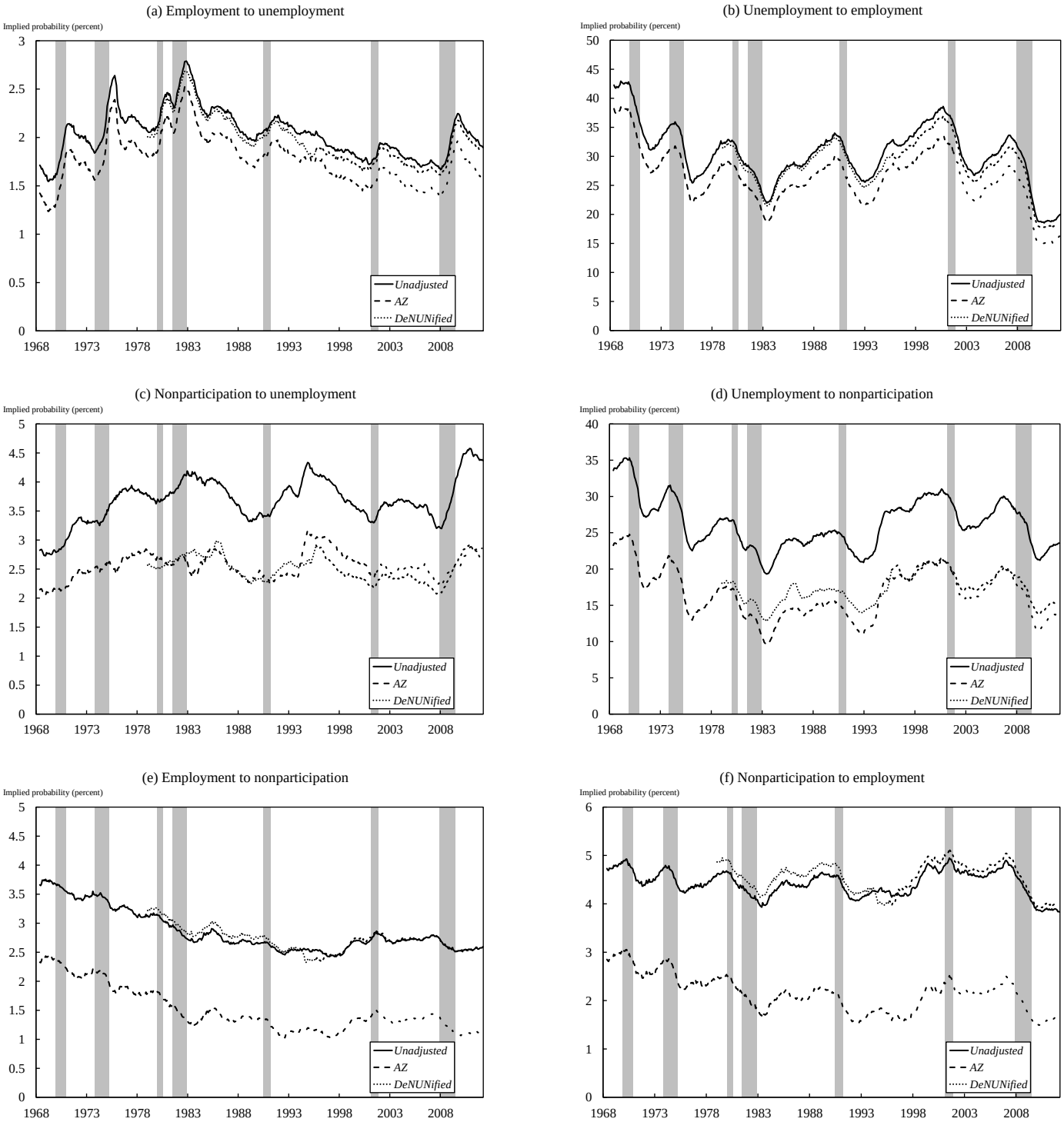
This *temporal aggregation* problem was noted by Darby, Haltiwanger and Plant (1985), and Shimer (2012, 2013) has provided a correction for this bias, which we summarize here. The task is to back out from estimates of the discrete-time transition probabilities p_{ij} corresponding estimates of the underlying instantaneous flow hazard rates, which we shall denote f_{ij}. In the Appendix, we show how the mapping between these takes a simple analytical form. The key point is that the underlying continuous-time flows must replicate the observed path of labor market stocks each period. This implies a tight link between the dynamics and steady states of the observed discrete-time flows p_{ij}, and their notional continuous-time counterparts f_{ij}. This mapping takes the convenient form of an eigendecomposition, and thereby allows one to infer all of the underlying flow hazards, f_{ij}.[12]

The impact of temporal aggregation bias on estimated worker flow probabilities can be seen in Figure 3. This plots the associated one-month transition probabilities implied by the time-aggregation correction, $1 - e^{-f_{ijt}}$. Consistent with the intuitive discussion at the beginning of this section, Figure 3 reveals that temporal aggregation in the raw gross flows misses some transitions, and incorrectly adds others. Specifically, the correction implies that the raw gross flows miss around 30 percent of inflows into unemployment, and 15 percent of outflows from unemployment to both employment and nonparticipation. In contrast, temporal aggregation in the raw gross flows leads to a slight overstatement of transitions between employment and nonparticipation.

The intuition for these results can be traced in large part to the magnitude of the probability of exiting unemployment in the United States. Figure 3 shows that unemployed

[12] A drawback of the approach is that it assumes that there is a contemporaneous mapping between an individual's labor market activities—working, searching, not searching—and their recorded labor market states—employment, unemployment and nonparticipation. In practice, there is a dynamic mapping between activities and recorded states. For example, to be recorded as unemployed, a respondent must have looked for work during the last month under the CPS definition. It is an important topic for future research to disentangle these more subtle time aggregation issues.

Figure 3: Implied monthly flow transition probabilities corrected for margin error and time aggregation: unadjusted and adjusted for spurious transitions



individuals flow into both employment and nonparticipation with an average probability of around 25 percent over the course of a month. As a result, the likelihood that an individual who flows into unemployment between CPS surveys exits unemployment prior to the next month's survey is nontrivial. Consequently, the raw gross flows will understate transitions in and out of unemployment. For the same reason, the overstatement of transitions between employment and nonparticipation in the gross flows data arises because an individual is more likely to experience an intervening unemployment spell when transitioning between these two states.

Aside from the effect of temporal aggregation on the estimated levels of worker flows, a notable feature of the adjusted flows in Figure 3 is that the cyclical properties of the corrected series are qualitatively unchanged. Importantly for the focus of this paper, the rate of outflow from unemployment to nonparticipation continues to fall during recessionary episodes after adjusting for temporal aggregation.

5 Measuring the role of the participation margin

With measures of the instantaneous transition rates f_{ij} in hand, we can use them to inform a decomposition of the time-series variance of each of the labor market stocks into parts accounted for by each of the respective flow hazards. In this section, we devise such a decomposition using analytical approximations to a partial-adjustment representation of labor market dynamics. We then apply this decomposition to the estimates of the flow hazards described above.

5.1 A three-state decomposition of unemployment fluctuations

In order to motivate our decomposition of variance, it is helpful first to formalize the mapping between the labor force stocks and flows. The latter takes the form of a simple discrete-time Markov chain,

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_t = \begin{bmatrix} 1 - p_{EU} - p_{EN} & p_{UE} & p_{NE} \\ p_{EU} & 1 - p_{UE} - p_{UN} & p_{NU} \\ p_{EN} & p_{UN} & 1 - p_{NE} - p_{NU} \end{bmatrix}_t \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t-1} . \tag{5}$$

This in turn can be simplified further by normalizing labor market stocks by the civilian non-institutional working-age population, $E_t + U_t + N_t \equiv 1$ for all t, so that E_t, U_t and N_t

are to be interpreted as shares of the population.[13] It follows that the three-equation system (5) can be rewritten as a two-dimensional system of the form

$$\underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_t}_{\mathbf{s}_t} = \underbrace{\begin{bmatrix} 1 - p_{EU} - p_{EN} - p_{NE} & p_{UE} - p_{NE} \\ p_{EU} - p_{NU} & 1 - p_{UE} - p_{UN} - p_{NU} \end{bmatrix}_t}_{\widetilde{\mathbf{P}}_t} \underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_{t-1}}_{\mathbf{s}_{t-1}} + \underbrace{\begin{bmatrix} p_{NE} \\ p_{NU} \end{bmatrix}_t}_{\mathbf{q}_t} \tag{6}$$

We denote the flow steady state of this Markov chain by $\bar{\mathbf{s}}_t = \left(\mathbf{I} - \widetilde{\mathbf{P}}_t\right)^{-1} \mathbf{q}_t$.

As in the two-state case described in Elsby, Hobijn, and Şahin (2013), changes over time in the flow hazards f_{ij} shift the discrete-time transition probabilities p_{ij}, as well as the steady state that the labor market is converging to, $\bar{\mathbf{s}}_t$. It is through this chain of events that changes in the underlying flows affect the path of employment and unemployment over time. We show in the Appendix that this intuition can be formalized in the form of the following partial-adjustment representation:

$$\Delta \mathbf{s}_t = \mathbf{A}_t \Delta \bar{\mathbf{s}}_t + \mathbf{B}_t \Delta \mathbf{s}_{t-1}, \tag{7}$$

where $\mathbf{A}_t = \left(\mathbf{I} - \widetilde{\mathbf{P}}_t\right)$ and $\mathbf{B}_t = \left(\mathbf{I} - \widetilde{\mathbf{P}}_t\right) \widetilde{\mathbf{P}}_{t-1} \left(\mathbf{I} - \widetilde{\mathbf{P}}_{t-1}\right)^{-1}$. The first term in (7) captures the changes in labor market stocks that are driven by contemporaneous changes in the flow transition rates which shift the flow steady state, $\bar{\mathbf{s}}_t$. The second term in equation (7) summarizes the transmission of past changes in transition rates onto the current labor market state.

This partial adjustment representation can be used to motivate a decomposition of variance for the change in labor market stocks over time, $\Delta \mathbf{s}_t$. To see how, note first that one can iterate backward on equation (7) to express $\Delta \mathbf{s}_t$ as a distributed lag of past changes in the steady-state labor market stocks $\Delta \bar{\mathbf{s}}_t$,

$$\Delta \mathbf{s}_t = \sum\nolimits_{k=0}^{t-1} \mathbf{C}_{k,t} \Delta \bar{\mathbf{s}}_{t-k} + \mathbf{D}_t \Delta \mathbf{s}_0, \tag{8}$$

where $\mathbf{C}_{k,t} = \left(\prod_{n=0}^{s-1} \mathbf{B}_{t-n}\right) \mathbf{A}_{t-k}$ and $\mathbf{D}_t = \prod_{k=0}^{t-1} \mathbf{B}_{t-k}$, and $\Delta \mathbf{s}_0$ is the change in labor market stocks in the first period of available data.

As we noted above, changes in the flow hazards f_{ij} shape the present and future evolution

[13] As mentioned in footnote 11, initially we ignore flows in and out of the population, and then make a small correction for margin error. Thus, implied labor market stocks in our flow analysis do in fact add up to the working-age population, as assumed in equation (6).

of $\Delta \mathbf{s}_t$ by shifting its flow-steady-state counterpart, $\Delta \bar{\mathbf{s}}_t$. Thus, to link changes in labor market stocks to changes in the flow hazards, we take a first-order approximation to the change in the steady-state labor market stocks,

$$\Delta \bar{\mathbf{s}}_t \approx \sum\nolimits_{i \neq j} \frac{\partial \bar{\mathbf{s}}_t}{\partial f_{ij_t}} \Delta f_{ij_t}, \tag{9}$$

where the approximation has been taken around the lagged flow hazard rates, $f_{ij_{t-1}}$. To compute the derivatives in equation (9), note that we can write the continuous-time analogue to the reduced-state Markov chain in (6) as

$$\dot{\mathbf{s}}_t = \underbrace{\begin{bmatrix} -f_{EU} - f_{EN} - f_{NE} & f_{UE} - f_{NE} \\ f_{EU} - f_{NU} & -f_{UE} - f_{UN} - f_{NU} \end{bmatrix}_t}_{\widetilde{\mathbf{F}}_t} \mathbf{s}_t + \underbrace{\begin{bmatrix} f_{NE} \\ f_{NU} \end{bmatrix}_t}_{\mathbf{g}_t}. \tag{10}$$

It follows that the flow steady state of the system can be rewritten as $\bar{\mathbf{s}}_t = -\widetilde{\mathbf{F}}^{-1}\mathbf{g}_t$. Using this, the associated derivatives in equation (9) are straightforward to compute analytically.

Piecing these components together yields the following decomposition of variance:

$$var\left(\Delta \mathbf{s}_t\right) \approx \sum\nolimits_{i \neq j} cov\left(\Delta \mathbf{s}_t, \sum\nolimits_{k=0}^{t-1} \mathbf{C}_{k,t} \frac{\partial \bar{\mathbf{s}}_{t-k}}{\partial f_{ij_{t-k}}} \Delta f_{ij_{t-k}}\right). \tag{11}$$

A direct implication of (11) is that one can compute the fraction of the variance in any given labor market stock variable accounted for by variation in any given flow transition hazard. For example, if one were interested in computing the contribution of changes in the employment-to-unemployment flow hazard, f_{EU}, to changes in the unemployment stock, then one could compute:

$$\beta_{EU}^{U} = \frac{cov\left(\Delta U_t, \left[\sum_{k=0}^{t-1} \mathbf{C}_{k,t} \frac{\partial \bar{\mathbf{s}}_{t-k}}{\partial f_{EU_{t-k}}} \Delta f_{EU_{t-k}}\right]_{2,1}\right)}{var\left(\Delta U_t\right)}. \tag{12}$$

Of course, the latter decomposition of variance applies to the stock of unemployed workers as a fraction of the working-age population, and therefore not directly to the unemployment rate, $u_t \equiv U_t / L_t$, where $L_t \equiv E_t + U_t$ is the labor force participation rate. However, it is straightforward to derive a decomposition of changes in u_t using the approximate transform,

$$\Delta u_t \approx \left(1 - u_{t-1}\right) \frac{\Delta U_t}{L_{t-1}} - u_{t-1} \frac{\Delta E_t}{L_{t-1}}. \tag{13}$$

Since the labor force participation rate is the sum of E_t and U_t, a decomposition of the labor force participation rate in terms of the contribution of changes in the flow hazards can be derived in a similar way to that of the unemployment rate.

5.2 Results

Table 3 summarizes the results of applying our decomposition to the estimates of the flow hazards f_{ij} derived above. It reports the shares of the variance of the unemployment rate accounted for by each f_{ij} based on both the unadjusted flows, as well as those adjusted for classification errors. Overall, the approach provides an accurate decomposition of unemployment variance, in the sense that the contributions of each flow sum approximately to one—the residual variance is generally less than 6 percent.

Consider first the results for the unadjusted gross flows estimates in the first row of Table 3. These confirm the well-known result that both countercyclical rates of job loss and procyclical rates of job finding account for a substantial fraction of the fluctuations in the aggregate unemployment rate. Over the whole sample period, around one-quarter of the cyclicality of the unemployment rate can be traced to the employment-to-unemployment hazard, and one-third to the unemployment-to-employment hazard, with a total contribution of approximately 60 percent. Thus, it is clear that an explanation of the processes of job loss and job finding is crucial to an understanding of the cyclical behavior of the labor market.

The next two columns of Table 3, however, reaffirm the visual impression of Figure 3 that the participation margin also accounts for a substantial fraction of the rise in unemployment during recessions. The combined contribution of flows between unemployment and nonparticipation accounts for around one-third of unemployment variation. Consistent with the countercyclicality of inflows into unemployment from nonparticipation, and the procyclicality of the U-to-N flow hazard, both flows matter. However, the U-to-N flow hazard contributes more than the N-to-U flow hazard.

Together, flows between unemployment and employment and flows between unemployment and nonparticipation explain the vast majority of unemployment movements; the indirect effect of flows between employment and nonparticipation is negligible.

The message of this analysis, then, is that the standard gross flows estimates of labor market transitions imply an economically-significant role for the participation margin. In what follows, we examine whether this baseline result is robust to the adjustments for classification error discussed earlier.

Table 3: Three-state variance decomposition of changes in the unemployment rate by classification error adjustment

Class. error adjustment	Start of sample	Share of variance							Total between		
		EU	UE	NU	UN	EN	NE	residual	U and E	U and N	E and N
Unadjusted	1967	24.9	34.9	9.5	23.9	-0.3	1.0	6.0	59.8	33.4	0.8
DeNUNified	1967	-	-	-	-	-	-	-	-	-	-
Abowd-Zellner	1967	29.6	41.7	-0.7	26.7	-1.3	2.1	1.8	71.4	26.0	0.8
Unadjusted	1978	22.3	35.1	13.2	22.3	-0.7	1.5	6.3	57.4	35.5	0.8
DeNUNified	1978	25.2	42.5	11.6	17.1	-0.8	1.1	3.3	67.7	28.7	0.3
Abowd-Zellner	1978	25.6	44.4	3.9	26.4	-1.7	2.3	-0.9	70.0	30.3	0.7

Note: Decomposition of variance of change in quarterly average of unemployment rate. All samples end in February 2012.

The remaining rows of Table 3 provide a quantitative sense of this. They implement the variance decomposition using the adjusted estimates of flow hazards based on the Abowd and Zellner (1985) method and the deNUNified flows. The contributions of flows between unemployment and employment are adjusted upward somewhat by both corrections, accounting for approximately two-thirds of unemployment fluctuations over the whole sample period. In addition, the variance contribution of flows from U to N remains in the neighborhood of 20 percent in the adjusted data. Consistent with the visual impression of Figure 3, and the message of equation (4), the estimated contribution of N-to-U flows is shaded down relative to the unadjusted gross flows data, especially for the AZ correction. Despite this, the joint contribution of the participation margin in the adjusted flows remains at around 30 percent of the variation in the unemployment rate. Thus, even after implementing adjustments for classification error, the participation margin is estimated to play a prominent role in driving cyclical unemployment dynamics.

It is instructive to compare these findings to prior literature that has focused on the respective roles of unemployment inflows and outflows in accounting for unemployment fluctuations in the context of a two-state framework. The results in Table 3 imply a joint variance contribution of unemployment outflows (the sum of the contributions of U-to-E and U-to-N flows) of approximately 60 percent for the unadjusted data, and 68 percent for the Abowd and Zellner (1985) correction. This is broadly consistent with the findings of earlier literature that has suggested something like a two-thirds outflows to one-third inflows decomposition of unemployment fluctuations (see for example Elsby, Michaels, and Solon, 2009; and Fujita and Ramey, 2009).[14]

6 Stock vs. flow decompositions: a stock-flow fallacy

The message of the above flows-based decomposition—that worker transitions between unemployment and nonparticipation contribute substantially to cyclical fluctuations in the unemployment rate—is a provocative one in the light of conventional wisdom. A prominent heuristic used to quantify the role of the participation margin in accounting for cyclical unemployment fluctuations is implicit in Figure 1. Specifically, a simple stocks-based decomposition of the variation in the unemployment rate can be derived from the following

[14] A drawback of the earlier two-state literature is that the estimated "inflow rate" into unemployment unavoidably conflates inflows from employment and nonparticipation respectively in a non-additive way. An advantage of the three-state decomposition provided in the present paper is that it disentangles these separate effects.

approximate relation,

$$\Delta u_t \approx (1 - u_{t-1}) (\Delta \log L_t - \Delta \log E_t) . \tag{14}$$

Thus, a close approximation to the change in the unemployment rate Δu_t is the difference in the logarithmic changes in the labor force participation rate $\Delta \log L_t$, and the employment-to-population ratio $\Delta \log E_t$.

Application of this stocks-based decomposition to quarterly averages of published labor market stocks from the Bureau of Labor Statistics for the period 1967 to 2012 implies a contribution of variance in the labor force participation rate to variance in the unemployment rate of

$$\beta_L^u = \frac{cov\left(\Delta u_t, (1 - u_{t-1}) \Delta \log L_t\right)}{var\left(\Delta u_t\right)} \approx -7 \text{ percent.} \tag{15}$$

This result stands in stark contrast to the implications of the flows-based decomposition summarized in Table 3. According to (15), the role of the participation margin is both quantitatively small, and of opposite sign, relative to that implied by the flows. The reason, of course, is that the labor force participation rate is mildly procyclical in the data. It follows that a simple stocks-based decomposition will suggest that the small declines in participation that accompany recessions in fact offset slightly the rise in unemployment. Comparisons of the relative cyclicality of labor market stocks, such as this, have informed a conventional wisdom that participation decisions are not of first-order importance for an understanding of unemployment fluctuations (see, for example, Lilien and Hall, 1986, and Hall, 2008, 2009). In the remainder of this section, we explain why this conclusion is an example of a stock-flow fallacy.

The key to understanding the seeming tension between these two approaches is to note that, in a dynamic labor market, the labor force participation rate is itself shaped by the underlying behavior of worker flows, just like the unemployment rate. By contrast, stocks-based and flows-based decompositions would deliver the same conclusion if the labor market were relatively static, which is the assumption implicit in a stocks-based analysis. For example, if recessionary declines in labor force participation were brought about by the movement of a small group of individuals from unemployment to nonparticipation that subsequently were reversed during times of recovery, increases in unemployment during recessions would be mitigated by an upward spike in the U-to-N hazard, and the two approaches would concur. Notwithstanding the fact that the U-to-N hazard in fact falls prominently during recessions, this view of the labor market also implies low levels of worker flows. Several decades of research on worker flows supports the exact opposite view, namely that worker

Table 4: Stocks-based decomposition of the rise in the unemployment rate in the twin recessions of the 1980s and the most recent downturn

Recessionary period	Cumulative change in		
	u	$\log L$	$\log E$
May 1979 to Dec 1982	0.052	0.013	−0.045
Mar 2007 to Oct 2009	0.056	−0.018	−0.079

flows are large, and that consequently the identities of individuals in each of the labor market states are shifting continually. Under this interpretation, the observed mild procyclicality of the participation rate is instead the outcome of a subtle interaction of offsetting cyclical movements in worker flow hazards.

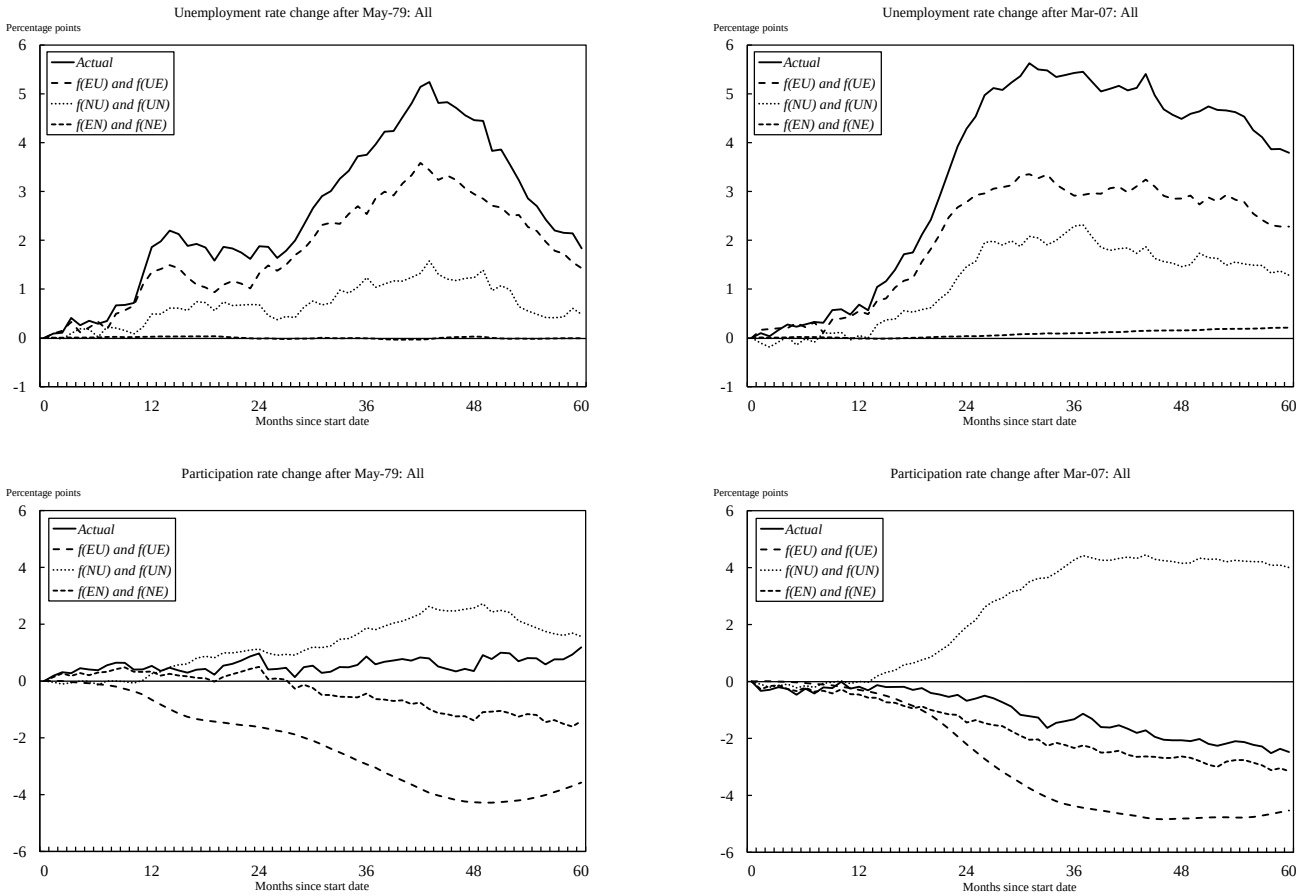
To illustrate this point, in the remainder of this section we present a case study that contrasts the twin recessions of the early 1980s with the Great Recession of the late 2000s. Both episodes were associated with a rise in the unemployment rate in excess of 5 percentage points. This is confirmed in Table 4, which reports the cumulative changes in the unemployment rate u, the log labor force participation rate $\log L$ and the log employment-to-population ratio $\log E$ respectively for the periods May 1979 to December 1982, and March 2007 to October 2009.

Viewed through the lens of the stocks-based decomposition in (15), Table 4 suggests that the contribution of the participation margin to unemployment fluctuations changed signs across the two episodes, reinforcing the rise in unemployment in the 1980s recessions, but moderating the rise during the Great Recession. The reason, of course, is that the labor force participation rate was rising as a trend phenomenon in the earlier episode, and now appears to be on a trend decline, as shown in Figure 1.

Should one conclude from this that the role of the participation margin in accounting for cyclical unemployment has shifted fundamentally as a result of these differing secular trends? The message from the worker flows is a resounding "no." Figure 4 presents the estimated contribution of each labor market flow to the changes in the unemployment rate during these two episodes. The role of flows between unemployment and nonparticipation is both quantitatively significant, and of similar magnitude, across the two recessionary periods, accounting for approximately one-third of the rise in the unemployment rate in each case.

To reconcile the divergent behavior of the participation rate across the two recessionary periods, we exploit a virtue of the flows-based decomposition in equation (11), namely that it can be applied to any combination of labor market stocks, including the labor force

Figure 4: Contributions of labor market flows to changes in stocks during the twin recessions of the 1980s and the most recent downturn



participation rate, $L \equiv E + U$. The final panels of Figure 4 present the analogous contributions of worker flows to the evolution of labor force participation. In both downturns, flows between unemployment and nonparticipation placed upward pressure on participation, consistent with the cyclical behavior of these flows discussed earlier. However, this tendency is almost exactly offset by the effect of flows between unemployment and employment. The intuition for the latter is somewhat subtle: Although the primary effect of flows between unemployment and employment in times of recession is to reduce employment and raise unemployment, unemployed workers are much more likely to leave the labor force compared to employed workers, that is $f_{UN} \gg f_{EN}$.[15]

[15] Alternatively, consider the implied *steady-state* labor force participation rate, $L^* = 1 - [(f_{EN}E^* + f_{UN}U^*) / (f_{NE} + f_{NU})]$. As employment falls and unemployment rises, more weight is placed on

The key to the different trajectories in participation between the 1980s recessions and the Great Recession, then, is the comparative effects of flows between *employment* and nonparticipation. In particular, these flows imparted a substantial negative effect on participation during the most recent downturn, while their effect was more muted in the early 1980s. This difference, which can be attributed to changing secular trends in the employment-to-nonparticipation flow rate in Figure 3, is what drives the opposite paths of the labor force participation rate across the two episodes. Since flows between employment and nonparticipation are largely neutral with respect to the unemployment rate, it would be fallacious to infer the contribution of the participation margin to recessionary increases in unemployment from the behavior of the stock of labor force participants, which is itself shaped by (different) worker flows.

7 Toward understanding the participation margin

The preceding sections have highlighted that the flow transition rates between unemployment and nonparticipation are prominently cyclical; that adjustments for classification errors and time aggregation do not eliminate this cyclicality; and that this variation contributes substantially to cyclical unemployment fluctuations. An important question, then, is what might explain the observed cyclicality of these flows. In this section, we assess a number of hypotheses for why the participation margin appears to be so important.[16] Our approach is to explore these hypotheses by delving into the pattern of heterogeneity in worker flows at the participation margin that can be observed in available data.

7.1 History dependence and labor force exit

The first channel that we explore is the role of cyclical shifts in the *labor force attachment* of the unemployment pool in accounting for the behavior of the average unemployment-to-nonparticipation[17] rate depicted in Figure 3. A stylized feature of recessions in the United

f_{UN} than its much smaller counterpart f_{EN}.

[16] A natural candidate explanation might be the role of extensions in the duration of unemployment insurance (UI) that accompany recessions, with the Great Recession of 2008 to 2010 being a prominent example. However, estimates of the impact of such UI extensions suggest a modest impact on unemployment (see Aaronson, Mazumder, and Schecter, 2010; Farber and Valletta, 2011; Fujita, 2010; Nakajima, 2012; Rothstein, 2011; Valletta and Kuang, 2010; and Valletta, 2010).

[17] We also examined the role of such compositional forces on other labor market flows, but found only modest effects on flows originating from employment and nonparticipation. The simple reason is that both the employment and nonparticipant stocks are much larger than the unemployment stock. Consequently,

States is the burst of job loss that occurs at the onset of a downturn. If such workers are more than averagely attached to the labor market, it is plausible that they will continue searching for employment rather than transitioning out of the labor force.

Data and measurement In what follows, we dig deeper into CPS microdata to study the role of compositional shifts in labor force attachment on the cyclicality of transitions between unemployment and out of the labor force. Since it is not possible to obtain a direct measure of labor force attachment, we use various proxies to study the relevance of this hypothesis. In addition to demographic characteristics (gender, age and education) and the reported reason for unemployment, we use the prior labor market status of individuals as proxies for labor force attachment. The latter revives an early insight of Akerlof and Main (1981) that, in practice, the structure of worker flow transitions may depart considerably from the descriptive first-order Markov structure in equation (5) that has informed the majority of research on labor market flows.[18] An important potential signal of labor market attachment would be *history dependence* in worker flows whereby individuals who have been attached to the labor market in the past exhibit a lower propensity to exit the labor force.

To facilitate an analysis of history dependence in worker flows, we exploit the full longitudinal dimension of the CPS by matching individual records across all eight months in sample. Recall from section 2 that the rotation structure of the CPS implies that each individual will thus be observed for two sets of four consecutive months, where the first of each set is separated by a year. Using these data, we compute U-to-N transition rates conditional on a full interaction of gender, age, education, reason for unemployment (job loser, job leaver, labor force entrant)[19] and past labor force status. Consistent with the rotation structure of the CPS, we define the latter as status one year prior to the survey.

Heterogeneity in labor force exit rates The second column of Table 5 reports U-to-N probabilities for each of these groups (though, for simplicity, not their interaction), averaged over the period 1979 to 2010.[20] Females, younger and older individuals, the less educated,

the composition of these larger stocks is influenced less by cyclical fluctuations.

[18] A recent exception is Gomes (2012), who highlights the existence of history dependence in worker flows in the United Kingdom.

[19] Further disaggregation of job losers into temporary layoffs and permanent job losers, and of labor force entrants into new entrants and re-entrants were not pursued because the 1994 CPS redesign led to important changes in the measurement of these subcategories.

[20] Note that these transition probabilities differ slightly from those reported in Figure 3. In particular, they are based on the raw transition probabilities computed from CPS microdata matched across all eight months in sample, and are not adjusted for margin error or temporal aggregation.

labor force entrants, and those who were not attached to the labor force in the past all are more likely to flow from unemployment to nonparticipation. Consistent with the hypothesis of this section, the common thread that unites these observations is that flows between unemployment and nonparticipation are more common among workers who tend to be less attached to the labor force.

Importantly, we also find that the composition of the unemployment pool becomes skewed towards more attached individuals during recessions. To provide a sense of this, we calculate the cumulative change in the unemployment share of each subgroup for each of the last five recessionary periods. The final column of Table 5 reports the simple average of these cumulative changes. During recessions, we observe increases in the unemployment shares of male, prime-aged workers who were attached to the labor force in the past. Since unemployed members of these groups are less likely to exit the labor force, these compositional shifts potentially could account for the observed decline in the average U-to-N flow rate during recessions.

The role of composition effects To quantify the magnitude of this compositional effect, we compute "counterfactual" U-to-N transition probabilities for each of the last five recessionary episodes. This counterfactual exercise is based on a "shift-share" analysis in the spirit of Shimer (1998, 2012). Note first that the aggregate unemployment-to-nonparticipation transition probability, p_{UN_t}, is a weighted average of transition probabilities for different groups of unemployed workers, $p_{UN_{it}}$:

$$p_{UN_t} \equiv \sum_i \omega_{it} p_{UN_{it}}. \tag{16}$$

Here, ω_{it} denotes the unemployment share of group i. To exploit fully the heterogeneity available in the data, in this analysis we consider the 216 groups implied by the *full interaction* of the groups reported in Table 5. To isolate the effect of changes in the composition of the unemployment pool, we examine the effects of holding composition fixed at its pre-recession distribution. Specifically, we compute the counterfactual transition probability

$$\text{Counterfactual } p_{UN_t} \equiv \sum_i \omega_{i0} p_{UN_{it}}, \tag{17}$$

where, ω_{i0} denotes the unemployment share of group i at the beginning of each recessionary episode. Table 6 reports the actual and counterfactual percentage declines in the U-to-N

Table 5: Heterogeneity in unemployment exit probabilities

Subgroup of the unemployed	Unemployment exit probability (%)			Change in unemployment share ω in recessions (%)
	p_{UN}	p_{UE}	$p_{UN} + p_{UE}$	
Gender:				
Men	17.8	27.1	44.9	4.7
Women	26.6	24.3	51.0	−4.7
Age:				
16 to 24	28.6	26.3	54.9	−6.4
25 to 54	17.5	26.2	43.7	5.4
55 and over	23.9	22.1	46.0	0.9
Education:				
Less than high school	28.5	23.5	52.0	−6.5
High school	19.1	26.0	45.1	3.1
Some college	20.1	28.3	48.3	1.8
College	15.4	28.2	43.6	1.5
Labor force status a year ago:				
Employed	14.7	31.6	46.3	3.0
Unemployed	19.4	19.8	39.2	2.4
Nonparticipant	36.6	20.5	57.0	−5.4
Reason for unemployment:				
Job leaver	19.7	29.2	48.9	−3.6
Job loser	13.3	28.2	41.5	12.4
Entrant	34.3	21.8	56.0	−8.8

Notes: Transition probabilities are calculated using Current Population Survey microdata matched across all eight months in sample. Changes in unemployment shares are calculated as the cumulative change in the unemployment share of each subgroup for each of the last five recessionary periods. The final column reports the simple average of these cumulative changes.

Table 6: Actual and counterfactual declines in unemployment exit probabilities by recession

Recessionary period	Percent change in p_{UN}		Percent change in $p_{UN} + p_{UE}$	
	Actual	Counterfactual	Actual	Counterfactual
1979Q2 to 1980Q3	−14.9	−1.6	−12.6	−8.2
1981Q2 to 1982Q4	−20.0	−6.5	−22.4	−17.7
1989Q1 to 1992Q2	−10.9	−2.0	−17.9	−14.1
2000Q4 to 2003Q2	−16.3	−7.3	−16.9	−11.6
2006Q4 to 2009Q4	−20.2	−6.0	−32.4	−27.8

Note: Authors' calculations using Current Population Survey microdata matched across all eight months in sample. Counterfactual declines are based on composition adjustment for the full interaction of the age, gender, education, labor force status one year prior, and reason for unemployment categories in Table 5.

transition probability over the course of each recessionary trough-to-peak ramp up in the unemployment rate since 1979.[21]

The message of Table 6 is that a large part of the cyclicality of U-to-N flows can be attributed to cyclical shifts in the composition of unemployed workers. In particular, depending on the recession, around 75 percent of the recessionary decline in the rate at which unemployed workers exit the labor force can be traced to compositional shifts.

This result is particularly striking given that the compositional adjustment in Table 6 is based on just a few observable factors—prior labor force status, reason for unemployment, age, education and gender. Since this small set of variables provides only imperfect proxies for labor force attachment, it is possible that additional unobservable dimensions of attachment would imply an even larger composition effect.

Recent research by Mueller (2012) also focuses on compositional changes in unemployment over the cycle, but highlights instead shifts in the *prior wages* of unemployed workers. Since survey questions pertaining to wages are asked only of one-quarter of the CPS sample (specifically, those in the fourth and eighth months in sample, the "outgoing rotation groups"), the addition of past wages yields sample sizes that are too small to estimate composition-adjusted flows with sufficient accuracy. However, consistent with the results of this section, Mueller documents that recessions are accompanied by shifts in the pool of unemployed workers towards those with higher wages in their previous job, and that these

[21] An alternative, regression-based approach would take each recessionary episode in turn (e.g. 2006Q4 to 2009Q4), focus on the subsample of unemployed workers, and regress an indicator for labor force exit on a full interaction of indicators for each of the subgroups, as well as a set of time dummies. The coefficients on the time dummies would be closely related to our "counterfactual" labor force exit rate series.

workers face lower transition rates from unemployment to nonparticipation (see Table 3 in Mueller, 2012). This finding suggests that controlling for shifts in prior wage of unemployed workers would further help in explaining the procyclicality of the U-to-N transition rate.

A noteworthy feature of the results reported in Table 6 is that they contrast with the prior analyses of Baker (1992) and Shimer (2012). While our counterfactual analysis focuses on the effect of compositional shifts on the *labor force exit* rate of unemployed workers, Baker's and Shimer's analyses focused instead on the *total* outflow rate from unemployment—that is, the *sum* of U-to-N and U-to-E transition rates. Their conclusion is that compositional shifts explain little of the fluctuations in the total unemployment outflow rate, seemingly in contrast to the message of Table 6.

To reconcile this apparent tension, recall that many of the characteristics used in Table 6 are intended to capture labor force attachment. A working hypothesis, then, is that the same characteristics that capture the propensity of an unemployed individual to continue searching (lowering the likelihood of a U-to-N transition) also render her more likely to find a job (raising the likelihood of a U-to-E transition).

This hypothesis is confirmed in Table 5, which includes parallel analyses of heterogeneity in the job-finding probability, p_{UE}. For example, while men, job losers and those attached to the labor force in the past on average face much lower rates of labor force exit p_{UN}, their job-finding rates p_{UE} tend to be moderately higher. As the unemployment pool becomes skewed towards these groups in recessions, the U-to-N transition probability is lowered, but the U-to-E rate is raised. An analysis of the effect of compositional shifts on the *total* outflow rate thus would find smaller effects due to these offsetting forces.

Table 6 confirms this intuition quantitatively. Consistent with the conclusion of Baker (1992) and Shimer (2012), and with the above hypothesis, it reveals that compositional shifts along the observable dimensions we measure account only for around one-quarter of recessionary declines in the total unemployment outflow rate $p_{UN} + p_{UE}$, much less than the compositional effect we highlight for labor force exit.

7.2 Labor force entry

Although the majority of the contribution of the participation margin to unemployment fluctuations is accounted for by cyclical changes in the rate of labor force exit from unemployment, Table 3 highlights that countercyclicality in labor force entry into unemployment also contributes. In this subsection, we assess available evidence for the role of various

channels that may account for this observation.

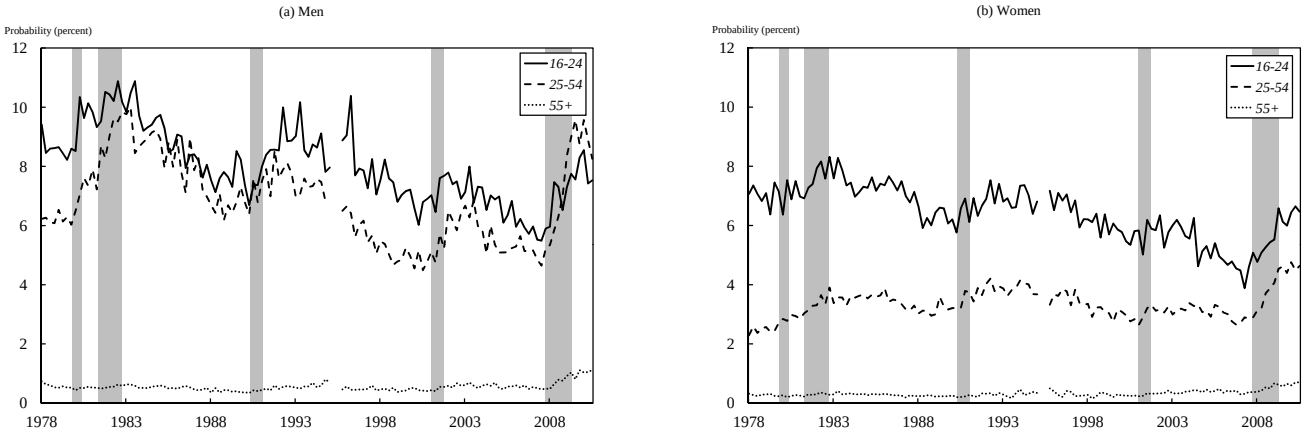
Classification error It is worth noting that our analysis thus far already provides a perspective on some of these hypotheses. First, a novel result of section 3 was to show how it is possible for the presence of classification errors to induce a countercyclical bias in measured transitions between unemployment and nonparticipation. The logic is that, since the majority of misclassification is between these two states, the population of nonemployed respondents at risk of being misclassified rises during recessions, so that measured worker flows between U and N tend to be overstated in downturns. Table 3 suggests that adjustments for classification error do reduce the contribution of labor force entry into unemployment somewhat. However, they do not eliminate the cyclicality of N-to-U flows, and the magnitude of the effect depends on the adjustment for spurious transitions. Thus, classification errors appear to provide only a partial account for the countercyclicality of labor force entry.

Time aggregation A second potential explanation for the countercyclicality of p_{NU} relates to time aggregation. An implication of the large magnitude of the job-finding rate in Figures 2 and 3 is that many job seekers are able to find jobs within the month between surveys. It thus seems plausible that reductions in rates of job finding during recessions may imply that labor force entrants are less likely to find a job during the month between surveys, leading to increases in realized N-to-U transitions. This mechanism, however, is implicit in the time aggregation adjustment that we implement. Inspection of Figures 2 and 3 reveals that these adjustments for time aggregation do little to dampen the cyclicality of the N-to-U rate.[22] Thus, time aggregation does not appear to contribute to the role of labor force entry.

Added worker effect The final channel we consider is the added worker effect. This is the idea that nonparticipant individuals within a household—typically the female partner—may begin to look for work during recessions to replace lost income arising from the job loss of another household member—typically the male partner. Since recessions are periods of relatively weak job-finding prospects, it is possible that such women will transition into unemployment as realized N-to-U flows.

[22] It is important to note that conventional time aggregation corrections—such as the one applied in this paper, and in the majority of recent literature on worker flows—invoke an assumption that the underlying flow hazards are constant across duration. If new labor force entrants were to face higher job-finding propensities than those who have been searching for some time, then it is possible that time aggregation has more prominent cyclical effects. See Krusell, Mukoyama, Rogerson and Şahin (2012) for an example of such a mechanism.

Figure 5: Nonparticipation-to-unemployment flow probabilities for men and women by age



Although an extensive analysis of the added worker effect is beyond the scope of our paper, a sense of its likely importance can be gained if we again use our data to delve into the heterogeneity of flows into unemployment due to labor force entry. Figure 5 plots the basic time series of p_{NU}, disaggregated by gender and age. A number of features of Figure 5 challenge the added worker effect channel. First, in terms of the levels of the flow rates, men are more likely than women to enter unemployment from out of the labor force. Most starkly, N-to-U rates among prime-aged men are double those among prime-aged women. Second, it is clear that the cyclicality of these flows is not a phenomenon driven by prime-aged women, the group most likely to account for the added worker effect. Rather, again we see that the cyclicality of p_{NU} appears to be larger among men than women, with prime-aged men being conspicuously cyclical.

The latter observations are intended to cast doubt on the role of the added worker effect as a leading account of the countercyclicality of aggregate labor force entry. It is important to note, however, that they are nonetheless consistent with the existence *to some degree* of an added worker effect, for which prior evidence provides some support. For example, using CPS data for the period 1994 to 2011, Mankart and Oikonomou (2012) estimate that an unemployment spell experienced by a male spouse increases the likelihood of his wife joining the labor force by 8 percentage points, or 67 percent.[23] Despite its microeconomic

[23]By contrast, Juhn and Potter's (2007) analysis of the added worker effect provides more mixed evidence. They find that labor market transitions of husbands and wives were negatively related in the 1960s and 1970s, but positively related in the 1990s and 2000s. They suggest that the added worker effect was important in the

significance, such an effect need not leave a significant imprint on the *aggregate* N-to-U rate that is the focus of this section: Married couples are only a subset of the population; the fraction of husbands that transition into unemployment at any point in time is small, even during recessions; and Figure 5 indicates that prime-aged and older women (who are more likely to be married) account for a small fraction of overall labor force entry.[24]

Taken together, then, the results of this section suggest that the cyclical behavior of rate of labor force entry into unemployment remains an important topic for further research.

8 Summary and discussion

An often-neglected empirical regularity in standard estimates of worker flows in the United States is that flows between unemployment and out of the labor force display prominent fluctuations over the business cycle. Moreover, these fluctuations at the participation margin contribute towards increasing unemployment in times of recession: Inflows into unemployment from nonparticipation rise in downturns; the rate at which jobseekers exit the labor force falls in times of recession.

In this paper, we have quantified the magnitude of this channel in accounting for cyclical unemployment, and considered its robustness to an array of adjustments for time aggregation in measured flows and classification errors in recorded labor market status. We have found that the contribution of the participation margin is quantitatively substantial, accounting for around one-third of cyclical unemployment movements. Moreover, this conclusion continues to hold after adjustments of the data to correct for spurious transitions. Finally, we have shown that, viewed through this lens, conventional wisdom on the participation margin informed by the cyclical behavior of labor market stocks is based on a stock-flow fallacy that implicitly neglects the role of worker flows in shaping the stock of labor force participants.

An important topic for further research, then, is to identify explanations for this phenomenon. We have highlighted one particular fruitful line of research. We have shown that a large part of the cyclical variation in worker flows at the participation margin can be traced to shifts in the composition of labor market attachment among the nonemployed in times of recession. The wave of job losses that accompanies the start of recessions skews the unemployment pool towards a group of workers who are more than averagely attached

1960s and 1970s when female labor force participation was lower, but that this effect largely disappeared in the 1990s and early 2000s as a consequence of rising female participation and positive assortative matching.

[24]Note also that Mankart and Oikonomou's (2012) calculations include transitions from nonparticipation to employment.

to the labor market, and can be expected to continue searching for employment rather than transitioning out of the labor force. We show that individuals who have been attached to the labor market in the past exhibit a lower propensity to exit the labor force, and that there are notable changes in the distribution of labor market attachment over the business cycle. This mechanism is quantitatively important—the majority of the cyclicality of unemployment-to-nonparticipation flows can be traced to the shift in the composition of unemployed workers towards more attached workers during the recessions.

In contrast, accounting for the countercyclicality of labor force entry into unemployment remains a challenge. While our analysis has shown that classification errors may partially explain this phenomenon, it also casts doubt on other commonly-cited channels, such as temporal aggregation and the added worker effect. Of particular note is that cyclical fluctuations in labor force entry are broad-based across both young and prime-aged, male and female workers. Further explanations to account for this phenomenon are needed.

In light of these results, it is tempting to conclude that future research should focus less on the cyclical variation in unemployment, and perhaps direct attention instead toward fluctuations in employment and nonemployment—that is, the sum of unemployment and nonparticipation. We argue that our results suggest a more nuanced set of conclusions.

First, the observation that marginally-attached workers are an important determinant of measured unemployment fluctuations at the participation margin tells us something about the underlying economics of labor market fluctuations. It suggests that worker heterogeneity is a crucial ingredient to an understanding of unemployment cyclicality. And, just as one would expect from simple economics, it is those workers on the margin that shape market outcomes.

Second, it is important to recognize that the presence of marginally-attached workers in the unemployment pool does not imply that cyclical fluctuations in unemployment are less meaningful. A key lesson of our analysis is that the labor market attachment of the unemployed is not constant over time—it *rises* in times of recession. Far from underscoring the irrelevance of unemployment fluctuations, the latter instead emphasizes the particular importance of unemployment in times of recession. And, it is again worth noting that this is precisely what simple economics would predict in a world with worker heterogeneity—that reductions in employment during recessions displace individuals into the jobless pool that are relatively attached to the labor market.

These observations echo the early work of Clark and Summers (1979), who were among the first to emphasize the fundamentally ambiguous distinction between unemployment and

nonparticipation. Nonetheless, they highlight the substantial heterogeneity in the experience of unemployment among the jobless, noting the importance of long spells in accounting for total unemployment. Our findings complement this view by stressing the roles of labor force attachment in generating long spells of unemployment, and of cyclical changes in the composition of attachment in shaping the cyclicality of unemployment.

Our conclusions also dovetail interestingly with recent theoretical research that has sought to provide a joint understanding of unemployment and labor force participation. A feature of much of this research is that it often has focused on devising models that can account for the cyclical comovement of labor market *stocks*.[25] While such research is a distinguished outlier relative to the abundance of theoretical and empirical research that has ignored the participation margin, our analysis emphasizes that the latter is a necessary, but not sufficient condition for a further desideratum, namely that our models provide an account of the cyclical behavior of underlying worker *flows*.

Toward that end, the recent work of Krusell, Mukoyama, Rogerson and Şahin (2012) has provided a theoretical framework that distils much of the economics suggested by our empirical analysis of worker flows. They demonstrate how a hybrid model of unemployment and labor supply is able to replicate both the levels and cyclical fluctuations in worker flows at the participation margin. Consistent with our empirical findings, worker heterogeneity, and the implied cyclical changes in the composition of the unemployment pool, play a crucial role in their model's ability to match worker flows at the participation margin.

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[25]See, for example, Tripier (2004); Veracierto (2008); Christiano et al. (2010); Galí et al. (2011); Ebell (2011); Haefke and Reiter (2011); Shimer (2011); and Campolmi and Gnocchi (2014).

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A Mathematical details

A.1 Derivation of equation (4)

Given the classification errors in equation (1), and under the assumption that $\varepsilon_{ij} = 0$ for all $ij \notin \{UN, NU\}$, measured flows between unemployment and nonparticipation can be written as

$$\begin{aligned} UN_t &= \varepsilon_{UU}\left[\varepsilon_{UN} UU_t^* + \varepsilon_{NN} UN_t^*\right] + \varepsilon_{NU}\left[\varepsilon_{UN} NU_t^* + \varepsilon_{NN} NN_t^*\right], \text{ and} \\ NU_t &= \varepsilon_{UN}\left[\varepsilon_{UU} UU_t^* + \varepsilon_{NU} UN_t^*\right] + \varepsilon_{NN}\left[\varepsilon_{UU} NU_t^* + \varepsilon_{NU} NN_t^*\right]. \end{aligned} \tag{18}$$

Noting that $\varepsilon_{UU} = 1 - \varepsilon_{UN}$, $\varepsilon_{NN} = 1 - \varepsilon_{NU}$, and that any product of the errors is second order in the presence of small ε_{UN} and ε_{NU} yields the approximation in equation (4).

A.2 Margin-error adjustment

We use the following method to adjust the transition probabilities that we get from the data to make them consistent with the labor market status vector, $\mathbf{s}_t$. Note that

$$\begin{aligned} \Delta \mathbf{s}_t &= \mathbf{s}_t - \mathbf{s}_{t-1} = \begin{bmatrix} -p_{EU} - p_{EN} & p_{UE} & p_{NE} \\ p_{EU} & -p_{UE} - p_{UN} & p_{NU} \end{bmatrix} \begin{bmatrix} E_{t-1} \\ U_{t-1} \\ N_{t-1} \end{bmatrix} \\ &= \begin{bmatrix} -E_{t-1} & -E_{t-1} & U_{t-1} & 0 & N_{t-1} & 0 \\ E_{t-1} & 0 & -U_{t-1} & -U_{t-1} & 0 & N_{t-1} \end{bmatrix} \begin{bmatrix} p_{EU} \\ p_{EN} \\ p_{UE} \\ p_{UN} \\ p_{NE} \\ p_{NU} \end{bmatrix} \\ &= \mathbf{X}_{t-1}\mathbf{p}. \end{aligned} \tag{19}$$

Note that the vector of transitional probabilities that we get from the data, which we denote by $\widehat{\mathbf{p}}$, has a covariance matrix that is proportional to a matrix that is consistently estimated using

$$\mathbf{W} = \begin{bmatrix} \frac{\widehat{p}_{EU}(1-\widehat{p}_{EU})}{E_{t-1}} & -\frac{\widehat{p}_{EU}\widehat{p}_{EN}}{e_{t-1}} & 0 & 0 & 0 & 0 \\ -\frac{\widehat{p}_{EU}\widehat{p}_{EN}}{E_{t-1}} & \frac{\widehat{p}_{EN}(1-\widehat{p}_{EN})}{E_{t-1}} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\widehat{p}_{UE}(1-\widehat{p}_{UE})}{U_{t-1}} & -\frac{\widehat{p}_{UE}\widehat{p}_{UN}}{U_{t-1}} & 0 & 0 \\ 0 & 0 & -\frac{\widehat{p}_{UE}\widehat{p}_{UN}}{U_{t-1}} & \frac{\widehat{p}_{UN}(1-\widehat{p}_{UN})}{U_{t-1}} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\widehat{p}_{NE}(1-\widehat{p}_{NE})}{N_{t-1}} & -\frac{\widehat{p}_{NE}\widehat{p}_{NU}}{N_{t-1}} \\ 0 & 0 & 0 & 0 & -\frac{\widehat{p}_{NE}\widehat{p}_{NU}}{N_{t-1}} & \frac{\widehat{p}_{NU}(1-\widehat{p}_{NU})}{N_{t-1}} \end{bmatrix}^{-1}. \tag{20}$$

We apply a weighted-restricted-least-squares adjustment method in the sense that we choose the vector of transition probabilities that are consistent with the labor market status vector, which we denote by $\mathbf{p}$, to

$$\text{minimize } \left(\mathbf{p} - \widehat{\mathbf{p}}\right)' \mathbf{W} \left(\mathbf{p} - \widehat{\mathbf{p}}\right), \text{ subject to } \Delta \mathbf{s}_t = \mathbf{X}_{t-1}\mathbf{p}. \tag{21}$$

Given the associated Lagrangian

$$L = (\mathbf{p}-\widehat{\mathbf{p}})' \mathbf{W} (\mathbf{p}-\widehat{\mathbf{p}}) - 2\mu' (\Delta \mathbf{s}_t - \mathbf{X}_{t-1}\mathbf{p}), \tag{22}$$

where μ is the 2×1-vector with Lagrange multipliers, it is fairly straightforward to derive that

$$\begin{bmatrix} \mathbf{p} \\ \mu \end{bmatrix} = \begin{bmatrix} \mathbf{W} & \mathbf{X}'_{t-1} \\ \mathbf{X}_{t-1} & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{W}\widehat{\mathbf{p}} \\ \Delta \mathbf{s}_t \end{bmatrix}. \tag{23}$$

Since all the terms on the right hand side are known, we can use this equation to adjust the transition probabilities to $\mathbf{p}$.

A.3 Temporal-aggregation correction

From equation (6), the discrete-time transition probabilities satisfy $\mathbf{s}_t = \widetilde{\mathbf{P}}_t \mathbf{s}_{t-1} + \mathbf{q}_t$. Similarly, from (10), the analogous continuous-time Markov chain is given by $\dot{\mathbf{s}}_t = \widetilde{\mathbf{F}}_t \mathbf{s}_t + \mathbf{g}_t$. Both of these systems imply a steady state $\bar{\mathbf{s}}_t$ that satisfies $\bar{\mathbf{s}}_t = -\widetilde{\mathbf{F}}_t^{-1}\mathbf{g}_t = -\widetilde{\mathbf{P}}_t^{-1}\mathbf{q}_t$. Let $\xi_t = (\mathbf{s}_t - \bar{\mathbf{s}}_t)$. Applying this transform to the discrete-time Markov chain, we can write $\xi_t = \widetilde{\mathbf{P}}_t \xi_{t-1}$. Likewise, using the continuous-time Markov chain, we can write $\dot{\xi}_t = \widetilde{\mathbf{F}}_t \xi_t$. The latter has solution $\xi_t = \mathbf{V}_t \mathbf{\Lambda}_t \mathbf{V}_t^{-1} \xi_{t-1}$, where $\mathbf{V}_t = [\bar{\mathbf{s}}_t, v_{1t}, v_{2t}]$ is the matrix of eigenvectors of $\widetilde{\mathbf{F}}_t$, $\mathbf{\Lambda} = diag\{1, e^{\lambda_{1t}}, e^{\lambda_{2t}}\}$, and λ_{it} denotes the associated eigenvalues of $\widetilde{\mathbf{F}}_t$. It follows that the discrete-time transition matrix is given by $\widetilde{\mathbf{P}}_t = \mathbf{V}_t \mathbf{\Lambda}_t \mathbf{V}_{\mathbf{t}}^{-\mathbf{1}}$. The latter implies that the eigenvectors of $\widetilde{\mathbf{P}}_t$ are the same as those of $\widetilde{\mathbf{F}}_t$, and that the eigenvalues of $\widetilde{\mathbf{P}}_t$ are equal to the exponentiated eigenvalues of $\widetilde{\mathbf{F}}_t$. Hence, given an estimate of $\widetilde{\mathbf{P}}_t$, one can infer the matrix of flow hazard rates $\widetilde{\mathbf{F}}_t$ via the above eigendecomposition.

A.4 Derivation of equation (7)

Note first that one can decompose the change in labor market state into parts,

$$\Delta \mathbf{s}_t = (\mathbf{s}_t - \bar{\mathbf{s}}_t) - (\mathbf{s}_{t-1} - \bar{\mathbf{s}}_{t-1}) + \Delta \bar{\mathbf{s}}_t. \tag{24}$$

Then note that the reduced Markov chain $\mathbf{s}_t = \widetilde{\mathbf{P}}_t \mathbf{s}_{t-1} + \mathbf{q}_t$ can be written as:

$$(\mathbf{s}_t - \bar{\mathbf{s}}_t) = \widetilde{\mathbf{P}}_t (\mathbf{s}_{t-1} - \bar{\mathbf{s}}_t) = \widetilde{\mathbf{P}}_t (\mathbf{s}_{t-1} - \bar{\mathbf{s}}_{t-1}) - \widetilde{\mathbf{P}}_t \Delta \bar{\mathbf{s}}_t. \tag{25}$$

Substituting for $(\mathbf{s}_t - \bar{\mathbf{s}}_t)$ in (24) implies:

$$\Delta \mathbf{s}_t = -\left(\mathbf{I} - \widetilde{\mathbf{P}}_t\right)(\mathbf{s}_{t-1} - \bar{\mathbf{s}}_{t-1}) + \left(\mathbf{I} - \widetilde{\mathbf{P}}_t\right)\Delta \bar{\mathbf{s}}_t. \tag{26}$$

Similarly, noting from (25) that $(\mathbf{s}_{t-1} - \bar{\mathbf{s}}_{t-1}) - \Delta \bar{\mathbf{s}}_t = \widetilde{\mathbf{P}}_t^{-1}(\mathbf{s}_t - \bar{\mathbf{s}}_t)$ implies that (24) can be rewritten as

$$\Delta \mathbf{s}_t = \left(\widetilde{\mathbf{P}}_t - \mathbf{I}\right)\widetilde{\mathbf{P}}_t^{-1}(\mathbf{s}_t - \bar{\mathbf{s}}_t).$$

Combining the latter with (26) confirms the proposed solution.