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U.S. Labor Market Dynamics Revisited

*Eran Yashiv**

Tel Aviv University, Tel Aviv 69978, Israel
yashiv@post.tau.ac.il

Abstract

The picture of U.S. labor market dynamics is opaque. This paper aims at its clarification by (i) listing data facts that can be agreed upon; these indicate that there is considerable cyclicality and volatility of both accessions to and separations from employment and hence both are important for the understanding of the business cycle; (ii) presenting the business-cycle facts of key series; (iii) pointing to specific gaps in the data picture, showing that the definite characterization of labor market dynamics depends upon the closing of these data gaps.

Keywords: Labor market dynamics; gross worker flows; job finding; separation; hiring; business cycles

JEL classification: *E*24; *J*63; *J*64

I. Introduction

The picture of U.S. labor market dynamics and its implications for the study of business cycles remain disturbingly opaque. These dynamics relate to the movement of workers (gross worker flows) between the states of employment, unemployment, and "out of the labor force". There are two, related issues of concern:

(i) Different empirical studies of U.S. labor market dynamics over the past two decades have yielded contradictory findings. Reading these different studies, it is not easy to get a sense of what the key data moments are and how they compare with each other.
(ii) Debates have emerged regarding the implications of gross worker flows for the understanding of the business cycle. The "conventional wisdom", based on the reading of Blanchard and Diamond (1989, 1990), Bleakley, Ferris and Fuhrer (1999) and Davis and Haltiwanger (1999),

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was that worker separations from jobs are the more dominant cyclical phenomenon than hiring of workers into jobs, and that therefore it is important to analyze the causes for separations. In particular, it was believed that in order to study the business cycle it is crucial to understand the spikes and volatility of employment destruction. This view was challenged by Hall (2005) and Shimer (2007), who claimed that separations are roughly constant over the cycle, and that the key to the understanding of the business cycle is in the cyclical behavior of the rate at which a worker finds a job. This challenging view has generated an active debate; see Yashiv (2007) for an extensive discussion.

Why are these concerns important?

First, in order to understand the operation of the labor market, it is crucial to get the facts right. In particular, we need to know what is to be explained in terms of co-movement, volatility and persistence of the key series. For example, the afore-cited debate refers to the question whether in recessions unemployment rises mostly because workers separate from employment, or because firms hire less, or because of both.

Second, for the study of business cycles two issues are central: driving impulses and propagation mechanisms. Whether shocks to job productivity are able to explain employment and unemployment fluctuations is a major question within the context of the first issue. These fluctuations are generated by the operation of gross worker flows and so understanding of the flows is linked with the study of the driving impulses. For the second issue of propagation mechanisms, it is essential to know what is the relative role of hiring and separation in employment changes. If one were to accept the Hall and Shimer idea of a constant rate of separation, then it is up to fluctuations in hiring rates to explain business cycles. The latter idea has led to exploration of the ability of the search and matching model of Pissarides (1985) and Mortensen and Pissarides (1994), a leading model in this context, to provide such an explanation. The finding of Shimer (2005) is that the standard model is unable to do so.[1] This result is due to the fact that fluctuations in job productivity do not translate—in the model—to the fluctuations in hiring, and hence in employment and unemployment, that we see in the data. Therefore, there is an important link between labor market dynamics and the explanation of cycles, or lack of it. The Shimer (2005) findings mean that we need a model of hiring that will perform better than the standard search and matching model.

Third, the determination of wages over the cycle is related to the transition rates of workers from unemployment to employment and of job vacancies from unfilled to filled. In a bargaining model if workers move

[1] For different analyses of this issue, see Yashiv (2006) and Mortensen and Nagypal (2007).

relatively easily from unemployment to employment, then their wages are likely to be relatively high. The behavior of these worker transition rates is at the heart of the afore-cited controversy, so they need to be better understood in order to explain wage behavior.

Finally, there are policy implications, such as the effectiveness of hiring subsidies, unemployment compensation, firing taxes and payroll taxes, which rest on the proper understanding of labor market dynamics. If hiring, for example, is important, then hiring subsidies could be a key policy tool; if separations are important, then firing taxes might be important.

This paper aims at clarifying the picture of U.S. labor market dynamics. It tries to determine what facts can be established, what are their implications for the business cycle, and what remains to be further investigated. The paper examines CPS data used by five key studies, as well as JOLTS data, both from the BLS, and establishes the key facts. In light of the findings it discusses the reasons for the contradictions between the earlier, "conventional" view and the Shimer–Hall challenge. The main contributions of the paper are: (i) to list data facts that can be agreed upon and their implications for understanding the business cycle; (ii) to present the business-cycle facts of the key series; and (iii) to point to specific, crucial gaps in the data picture.

The paper proceeds as follows. Section II gives the necessary background by looking at the dynamic equations of the labor market and determining the key flows to be studied. The claims made in the literature regarding these flows are summarized. Data sources and measurement issues are discussed in Section III. The latter discussion facilitates explanation of the disparities across studies which use the same data source. Section IV undertakes cyclical analysis of the data. It attempts to draw findings that are robust across studies, as well as to delineate the differences. Section V examines more closely some additional data features that do not pertain to cycles but are important for labor market dynamics. Section VI concludes by discussing the key facts that can be agreed upon and their implications, as well as by delineating the issues in need of further study.

II. The Issues

I begin by looking at the equations describing gross flows. These serve to clarify the key concepts and variables to be examined. I then summarize how the thinking in the literature on these labor market dynamics has evolved.

Labor Market Dynamics: Basic Equations

The dynamic equations of the labor market recognize the fact that in addition to the official pool of unemployed workers, to be denoted U, there is another relevant pool of non-employed workers—the "out of the labor force" category, to be denoted N, and that there are substantial flows between the latter and the employment pool E. Flows between these states are to be denoted as follows: M_t^{UE} and M_t^{NE} for hiring flows into employment from unemployment and from out of the labor force, respectively, S_t^{EU} and S_t^{EN} for the corresponding separation flows out of employment.

Unemployment dynamics are given by:

$$U_{t+1} = U_t\left(1 - p_t^{UE}\right) + \delta_t^{EU} E_t + F_t^{NU} - F_t^{UN}, \tag{1}$$

where p^{UE} is the job-finding rate (moving from unemployment to employment), $\delta^{EU} = S^{EU}/E$ is the separation rate from employment, and $F_t^{NU} - F_t^{UN}$ is the net inflow of workers from out of the labor force joining the unemployment pool (computed by deducting the gross flow out of unemployment from the gross flow into it).

In steady state there is a constant growth rate of unemployment at the rate of labor force growth, to be denoted g^L, and the unemployment rate is constant at $\overline{u}$, so steady-state unemployment is given by:

$$\overline{u} = \frac{\dfrac{F^{NU} - F^{UN}}{L} + \delta^{EU}}{p^{UE} + g^L + \delta^{EU}}, \tag{2}$$

where the labor force is $L \equiv E + U$.

In case there is no labor force growth or workers joining from out of the labor force, i.e., $(F^{NU} - F^{UN})/L = g^L = 0$, this becomes:

$$\overline{u} = \frac{\delta^{EU}}{\delta^{EU} + p^{UE}}. \tag{3}$$

Given that $M_t^{UE} = p_t^{UE} U_t$ and $\delta_t^{EU} = S_t^{EU}/E_t$, the empirical researcher needs data on the stocks U_t and E_t and on the flows M_t^{UE} and S_t^{EU}, to investigate the determinants of $\overline{u}$.

Note three implications of these equations: (i) Taking the whole employment stock, E, as one pool to be explained, it is flows to and from this pool that need to be accounted for. Flows within E (job to job) do not change E itself. In what follows, the term "separations" will refer to separations from E and "hires" will refer to hiring into E, and not to separations or hires within E. This is an important distinction, as some studies focused on separation from employment δ^{EU+EN} while others focused on total separations $\delta^{EU+EN+EE}$. (ii) Another important distinction is between hiring rates M^{UE}/E and job-finding rates $p^{UE} = M^{UE}/U$; some studies compared the separation rate from employment δ^{EU} to the former, while others emphasized the comparison to the latter. (iii) The key variables for understanding the rate of unemployment at the steady state are p^{UE}, δ^{EU}, $(F^{NU} - F^{UN})/L$ and g^L. In the next sections I study their behavior.

Interpretation of the Data and Emerging Questions

I briefly summarize the interpretation given in the literature to the gross worker flows data—the variables M^{UE}, M^{NE}, S^{EU}, S^{EN}—in accounting for U.S. labor market dynamics.

Trend. Ritter (1993) and Bleakley *et al.* (1999) report a downward trend in flows in and out of employment and in job-finding and separation rates since the early 1980s.

Volatility. Blanchard and Diamond (1989, 1990) found that the amplitude of fluctuations in the flow out of employment is larger than that of the flow into employment, implying that changes in employment are dominated by movements in job destruction rather than in job creation. Bleakley *et al.* (1999) found that once the trend is removed, the flows out of employment have more than twice the variance of the flows into employment. These studies place the emphasis on comparing hiring rates (M^{UE}/E) to the separation rate from employment (δ^{EU}). But recently Shimer (2007) and Hall (2005) claimed that separation rates (δ) are not as volatile as job-finding rates ($p^{UE} = M^{UE}/U$) and that they can be taken, roughly, as constant (in detrended terms).

Cyclicality. Blanchard and Diamond (1989, 1990) found sharp differences between the cyclical behavior of the various flows. In particular, the *EU* flow increases in a recession while the *EN* flow decreases; the *UE* flow increases in a recession, while the *NE* flow decreases. Ritter (1993) reported that the net drop in employment during recessions is clearly dominated by job separations. Bleakley *et al.* (1999) found that the flow due to voluntary quits declines fairly sharply during recessions, consistent with the notion that quits are largely motivated by prospects for finding another job. "Involuntary" separations—both layoffs and terminations—rise sharply during recessions and gradually taper off during the expansions that follow. Using these data as well as other data sets, Hall (1995) too stresses the importance of separations for cyclical dynamics (see, for example, his conclusions on p. 266).

Recently, some authors have presented a new picture of worker flows cyclicality. Hall (2005) developed estimates of separation rates and job-finding rates for the past 50 years, using historical data informed by the detailed recent data from JOLTS. He found that the separation rate is nearly constant while the job-finding rate shows high volatility at business-cycle and lower frequencies.[2] Another important finding from the new data is

[2] Hall (2005) does make two remarks: one is that the CPS direct measure of separations is on average about 7 percent per month, much higher than the other estimates, which are a

that a large fraction of workers departing jobs move to new jobs without intervening unemployment. In similar vein, Shimer (2007) reported that the job-finding probability is strongly procyclical while the separation probability is nearly acyclical, particularly during the last two decades. He showed that these results are not due to compositional changes in the pool of searching workers, nor are they due to movements of workers in and out of the labor force. Both concluded that the results contradict the conventional wisdom of the last 15 years. If one wants to understand fluctuations in unemployment, one must understand fluctuations in the transition rate from unemployment to employment, not fluctuations in the separation rate. Note, that Hall (2005) and Shimer (2007) focus on comparing p and δ, rather than M/E and δ.

This challenging view has met with a number of replies. Davis (2005) showed that understating the cyclical variation in the separation rate would lead to an overstatement of the cyclical variation in the job-finding rate. Relying on fluctuations mostly in the job-finding rate to explain labor market outcomes leads to counterfactual implications. Simulating a drop in the job-finding rate as in a recession but with no change in the separation rate, he shows (see his Figure 2.17 and the discussion on pp. 142–144) the following: the E to U flow rises too little relative to the data, and the U to E flow falls too much relative to the data. The way to obtain results in accordance with the data is to posit a sharp rise in the separation rate. Fujita and Ramey (2006) construct a decomposition of unemployment variability which contradicts Shimer's (2007) conclusions. They find that separation rates are highly countercyclical under alternative cyclical measures and filtering methods and that fluctuations in separation rates contribute substantially to overall unemployment variability. Elsby, Michaels and Solon (2007) show that even with Shimer's (2007) methods and data there is an important role for countercyclical inflows into unemployment. Their conclusions are further strengthened when they refine Shimer's methods of correcting CPS labor force series for the 1994 redesign and for time aggregation and undertake a disaggregated analysis.

In what follows I look at the data attempting to reconcile some of the differences in interpretation and to establish a consistent picture.

III. The Data

Understanding U.S. data on labor market dynamics requires an appreciation of the measurement issues involved. I discuss the data sources and then

bit over 3 percent (his pp. 110–111); the other is that the data on separations come from different sources showing different patterns and the evidence is not strong (his pp. 112 and 113).

the key measurement issues. I go on to explain why these issues may lead to data series being computed differently on the basis of the same source.

Data Sources

There are two main sources for U.S. aggregate worker flow data: the Current Population Survey (CPS) and the Job Openings and Labor Turnover Survey (JOLTS), both of the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor. Their properties are discussed in the Appendix. CPS data were computed and analyzed by Blanchard and Diamond (1989, 1990), Ritter (1993), Bleakley *et al.* (1999),[3] Fallick and Fleischmann (2004) and Shimer (2007).[4] Note that what is done below is not the analysis of the raw CPS data but rather the analysis of the computed data, i.e., the computed gross flows, based on CPS, as undertaken by the cited authors.[5]

Measurement Issues

The CPS is a rotating panel, with each household in the survey participating for four consecutive months, rotated out for eight months, then included again for four months. With this structure of the survey, not more than three-quarters of survey respondents can be matched, and typically the fraction is lower because of survey dropouts and non-responses. Using these matched records, the gross flows can be constructed. However, there are various problems that need to be addressed when doing so.

Abowd and Zellner (1985) and Poterba and Summers (1986) have found that missing observations and classification problems lead to a significant number of spurious transitions in the data. The former problem arises as households move out of the sample and individuals move out of households remaining in the sample. Thus, some interviewees of one month are not located in the prior or in the following month. The misclassification problem arises as CPS interviewers or respondents may "check off the wrong boxes" and misclassify an individual's labor force status. If this misclassification is corrected in the second month by correctly coding the labor

[3] Updated further till 2003:12, communicated personally by the authors.
[4] For the Shimer data see Shimer (2007) and his web page http://robert.shimer.googlepages.com/flows. The data from June 1967 and December 1975 were tabulated by Joe Ritter and made available by Hoyt Bleakley.
[5] A summary of data sources and a discussion of them is to be found in Davis and Haltiwanger (1998, 1999), Fallick and Fleischmann (2004) and Davis, Faberman and Haltiwanger (2006). Hall (1995, in particular p. 233) places the CPS data in the context of other data sets.

force status (or if the reverse is true), then a spurious transition is recorded. These two problems bias the measured flows, generating measurement noise beyond conventional sampling error. By using information from the CPS reinterview surveys, the above researchers estimated the amount of misclassification occurring with flows between E, N and U. Abowd and Zellner (1985) make two sets of corrections: (i) allocating missing data to the unadjusted gross flows using a fixed allocation pattern so the time-series behavior of the implied stocks—E, U and N—fits the time series of the actual stocks as closely as possible; (ii) using reinterview survey information to correct for classification error.

Shimer (2007) discusses the issue of time aggregation. When the job-finding rate is high, a worker who loses a job is more likely to find a new one without experiencing a measured spell of unemployment. A continuous-time framework allows workers to lose a job and find another within the period. These separations are missed in a discrete time equation, so the latter yields fewer separations and a negative bias in the measured correlation between the job-finding and separation rates.

Additional issues involve methods of matching individuals across months, weighting individuals, aggregation across sectors, survey methodology changes (in particular the 1994 CPS redesign) and seasonal adjustment. The above studies, as well as the five studies which data are examined here, offer extensive discussion.

Why Data Series May Differ

In the next section I present an analysis of five data sets, computed by different authors on the basis of raw CPS data. They turn out not to be the same. Why is this so? The preceding discussion makes it clear that there are various measurement issues that need to be treated. It is evident that if treatment methods vary then the resulting series will differ. The discussion in Bleakley *et al.* (1999, pp. 72–76) gives important details about these adjustments. As key examples, consider the following points which emerge from this discussion.

Adjustments are Substantial. The Abowd–Zellner adjustments for misclassification substantially reduce the transitions between labor market states. The NE flows have the largest reduction, almost 50 percent.

Application of Adjustment Methods May Vary. The different authors have not used the same corrections of the data. One striking example is the use of fixed Abowd–Zellner adjustment factors despite evidence of time variation in these factors; see Bleakley *et al.* (1999, p. 75).[6] Another example is the use by Bleakley *et al.* (1999) of additional adjustments, dealing with the 1994 CPS redesign.

Seasonal Adjustment May Vary. The gross flows data exhibit very high seasonal variation; see, for example, the discussion of Tables 1 and 2 in Bleakley *et al.* (1999). The methodology of seasonally adjusting the series differs across studies: Blanchard and Diamond (1990) use the Census Bureau X11 program. Ritter (1993) also seasonally adjusts using the X11 procedure but further smooths using a five-month centered moving average. Bleakley *et al.* (1999) note the use of regressions on monthly dummies as well as the X11 methodology. Fallick and Fleischmann (2004) use the newer Census Bureau X12 seasonal adjustment program. Shimer (2007) uses a ratio-to-moving-average technique.

Hence, even though the data source may be the same, the resulting series may differ depending upon the differential application of adjustments.

IV. Cyclical Properties of the Data

I take the data series as computed by the authors of the afore-cited five key studies from raw CPS data, as well as the more recent JOLTS data. The aim is to try to come up with a consistent picture of gross worker flows from these six data sets. While doing so I find differences between the data sets, as would be expected following the discussion above. I present the first two moments of the data and then undertake cyclical analysis. Subsequently I look at the dynamics of unemployment and their relation to the job-finding and separation rates.

Key Moments of the Gross Flows Data

Table 1 presents the first two moments of the gross flows data.[7] For JOLTS there are two relevant flow series—$M^{UE+NE+EE}$ and $S^{EU+EN+EE}$, i.e., job-to-job flows are included. The key findings are as follows.

Flows into Employment. Panel (a) of Table 1 shows flows into employment. A number of features stand out: for flows from unemployment, four

[6] This discussion makes it clear that Abowd–Zellner adjustments depend on time-varying factors, with the possible implication that they will be applied differently by different authors.
[7] While all data series are originally monthly, where noted they are presented as quarterly averages in monthly terms. In the case of the Shimer (2007) data, for the most part I use one data set. But in some cases I derived an implied series by a relevant manipulation of the data or used a second, somewhat different, computation from the same paper, which I denote “Shimer II”. These are defined in the relevant places below.

Table 1. *Moments of the gross flows*

(a) Hiring flows to employment

Study	Sample	M^{UE}/E		$p^{UE}=(M^{UE}/U)$		M^{NE}/E		M^{UE+NE}/E	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
BD (1989, 1990)	1968:1–1986:5	0.017	0.002	0.257	0.053	0.015	0.002	0.033	0.002
R (1993)	1967:6–1993:5	0.017	0.002	0.263	0.046	0.029	0.004	0.046	0.003
BFF (1999)	1976:2–2003:12	0.016	0.002	0.247	0.030	0.013	0.001	0.030	0.003
FF (2004)	1994:1–2004:12	0.015	0.001	0.288	0.029	0.025	0.002	0.040	0.002
S (2007)	1967:4–2004:12	0.020	0.003	0.321	0.050	—	—	—	—
								$\frac{M^{UE+NE+EE}}{E}$	
J	2000:12–2005:06	—	—	—	—	—	—	0.032	0.002

(b) Separation flows from employment

Study	Sample	δ^{EU}		δ^{EN}		δ^{EN+EU}	
		Mean	Std.	Mean	Std.	Mean	Std.
BD (1989, 1990)	1968:1–1986:5	0.014	0.003	0.017	0.002	0.031	0.002
R (1993)	1967:6–1993:5	0.015	0.003	0.032	0.004	0.047	0.003
BFF (1999)	1976:2–2003:12	0.013	0.002	0.015	0.001	0.029	0.003
FF (2004)	1994:1–2004:12	0.013	0.001	0.027	0.002	0.040	0.002
S (2007)	1967:4–2004:12	0.020	0.003	0.030	0.004	0.050	0.005
S II (2007)	1951:1–2004:12					0.035	0.005
						$\delta^{EN+EU+EE}$	
J	2000:12–2005:06	—	—	—	—	0.031	0.001

Notes: BD stands for Blanchard and Diamond, R for Ritter, BFF for Bleakley, Ferris and Fuhrer, FF for Fallick and Fleischmann, S for Shimer, S II for another computation from that same reference (see Note d to Table 3 below), and J for JOLTS. All data are the relevant flows as adjusted by the authors, and are divided by seasonally-adjusted employment; they are monthly except for the Shimer (2007) data, which are quarterly averages of monthly data.

studies depict very similar time series while the series from Shimer (2007) are somewhat higher, due to the fact that he captures more transitions by correcting for time aggregation. The monthly job-finding rate ($p^{UE}=M^{UE}/U$) is around 25–32 percent on average. Flows from out of the labor force are as sizable as flows from unemployment. For these *NE* flows there seem to be two groups of studies: Blanchard and Diamond (1989) and Bleakley *et al.* (1999) report mean hiring rates that are lower than those of Ritter (1993) and Fallick and Fleischmann (2004). The JOLTS series of total hires, which also includes *E* to *E* flows, lies between these two groups of studies but is quite dissimilar.

Flows Out of Employment. Panel (b) of Table 1 shows flows out of employment. Here again the Shimer rates are higher than the others and the

EN flows are measured differentially across studies. The JOLTS series, including *EE* flows, lies once more between the two groups. The mean total separation rate ranges from around 3 percent a month according to three sources to as high as 5 percent according to Shimer. Note that even small differences in separation rates still imply sizable differences in the number of workers separating.

Comparing the Data Sets. As the aforegoing analysis has revealed differences across data sets, Table 2 looks at the pairwise correlations between selected series, with all series filtered by a low-frequency HP filter.[8]

Panel (a) looks only at flows between U and E. Most of the correlations of the p^{UE} and of the δ^{EU} series are very high, as can be expected from the finding that the different studies yield similar series for these flows. Panel (b) looks at total flows—both between U and E and between N and E—in terms of M/E and δ. Here the pairwise correlations are much lower, reflecting the substantial differences across the different computations of the flows between N and E. The negative or low positive correlations of JOLTS with the other series probably reflect the fact that it contains the *EE* flows while the others do not.

The Cyclical Behavior of Flows

A key issue in the cited literature is the cyclical properties of these flows. Table 3 reports correlations and relative standard deviations of hiring rates, job-finding rates[9] and separation rates with real GDP. Figure 1 plots selected series.

Panel (a) of Table 3 uses the Bleakley *et al.* (1999) data with four alternative detrending methods (all on the logged series): first differences, the Hodrick–Prescott (HP) filter with the standard smoothing parameter ($\lambda = 1{,}600$), with a low frequency filter ($\lambda = 10^5$), and the Baxter–King (BK) band-pass filter. Panel (b) reports the results for the other data sets using the HP filter with the standard smoothing parameter ($\lambda = 1{,}600$); computations of the other filters for these data sets are available from the author. Panel (c) uses the Shimer (2007) data to report cross-correlations. The Appendix provides a discussion of these filtering techniques and their effects in the current context.

Table 3 and Figure 1 indicate the following patterns, all with respect to real GDP.

[8] The correlations for Fallick and Fleischmann and JOLTS series should be interpreted with care as the original series are very short time series.

[9] It is not obvious what would be a correct measure of aggregate p, i.e., incorporating both p^{UE} and p^{NE}. See Section V.

Table 2. *Pairwise correlations*

(a) Flows between *U* and *E*

	p^{UE}					δ^{EU}				
	BD	Ritter	BFF	FF	S	BD	Ritter	BFF	FF	S
BD (1989)	1					1				
R (1993)	0.88	1				0.91	1			
BFF (1999)	0.72	0.93	1			0.81	0.95	1		
FF (2004)	NA	NA	0.86	1		NA	NA	0.62	1	
S (2007)	0.76	0.88	0.91	0.84	1	0.86	0.94	0.84	0.53	1

(b) Flows between *U*, *N* and *E*

	M^{UE+NE}/E					δ^{EU+EN}						
	BD	R	BFF	FF	JOLTS	BD	R	BFF	FF	S I	S II	JOLTS
BD (1989)	1					1						
R (1993)	0.68	1				0.77	1					
BFF (1999)	0.62	0.81	1			0.69	0.88	1				
FF (2004)	NA	NA	0.65	1		NA	NA	0.26	1			
S (2007) I						0.63	0.82	0.58	0.50	1		
S (2007) II						0.37	0.54	0.51	0.21	0.50	1	
JOLTS (incl. *EE*)	NA	NA	−0.57	−0.14	1	NA	NA	−0.29	0.61	0.33	0.39	1

Notes: See notes to Table 1. The series are logged and filtered by an HP filter with smoothing parameter 10^5.

Table 3. *Business cycle properties*

(a) Full analysis

BFF (1999)	1st diff.		HP (1,600)		HP (10^5)		BK	
1976:I–2003:IV	ρ	$\sigma\cdot/\sigma_y$	ρ	$\sigma\cdot/\sigma_y$	ρ	$\sigma\cdot/\sigma_y$	ρ	$\sigma\cdot/\sigma_y$
$M^{UE}/E, y$	−0.23	6.9	−0.68	3.9	−0.82	3.7	−0.84	3.4
$M^{NE}/E, y$	0.06	7.1	0.31	2.8	0.44	2.2	0.54	2.0
$(M^{UE}+M^{NE})/E, y$	−0.12	5.9	−0.43	2.5	−0.59	2.1	−0.66	1.7
p^{UE}, y	0.31	7.3	0.76	4.5	0.83	4.8	0.89	4.1
δ^{EU}, y	−0.41	8.4	−0.77	4.9	−0.84	4.7	−0.88	4.4
δ^{EN}, y	−0.01	6.3	0.35	2.5	0.40	1.9	0.65	1.8
δ^{EU+EN}, y	−0.28	6.1	−0.53	2.6	−0.66	2.3	−0.71	1.8

(b) Abridged analysis (HP filter 1,600)

	BD (1989, 1990)		R (1993)		FF (2004)		S (2007)	
	ρ	$\sigma\cdot/\sigma_y$	ρ	$\sigma\cdot/\sigma_y$	ρ	$\sigma\cdot/\sigma_y$	ρ	$\sigma\cdot/\sigma_y$
$M^{UE}/E, y$	−0.75	4.4	−0.70	4.3	−0.45	4.6	−0.72	3.9
$M^{NE}/E, y$	0.56	4.9	0.33	2.2	0.26	5.2	—	—
$(M^{UE}+M^{NE})/E, y$	−0.20	2.6	−0.37	1.9	0.01	3.5	—	—
p^{UE}, y	0.80	3.7	0.75	4.4	0.83	6.0	0.75	5.1
p^{UE+NE}, y	—	—	—	—	—	—	0.20	2.2
JF, y	—	—	—	—	—	—	0.83	4.9
δ^{EU}, y	−0.81	7.2	−0.80	5.7	−0.48	6.3	−0.70	4.7
δ^{EN}, y	0.54	4.6	0.41	1.9	0.33	4.6	0.38	2.4
δ^{EU+EN}, y	−0.41	3.0	−0.50	1.8	0.02	3.6	−0.35	2.2
Sample	1968:I–1986:II		1967:II–1993:II		1994:I–2004:IV		1967:II–2004:IV	

Continued

Table 3. (Continued)

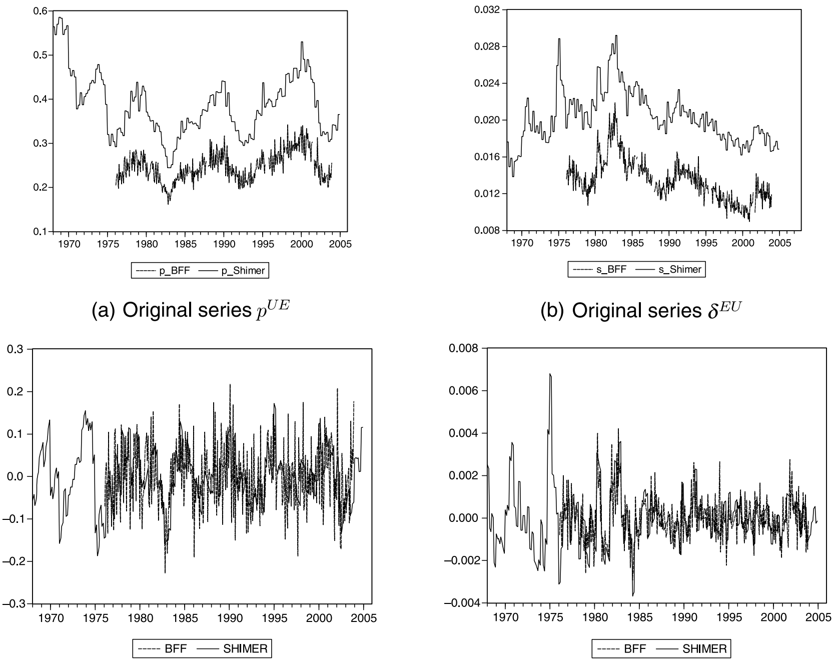
(c) Cross-correlations analysis—Shimer (2007) data

	Lags					Leads			
j	12	6	3	1	0	1	3	6	12
$JF_{t\pm j}, y_t$	−0.16	0.20	0.57	0.80	0.87	0.87	0.72	0.25	−0.35
$p^{UE+NE}_{t\pm j}, y_t$	−0.21	−0.03	0.15	0.28	0.33	0.40	0.41	0.26	−0.10
$p^{UE}_{t\pm j}, y_t$	−0.23	0.09	0.47	0.73	0.80	0.84	0.72	0.28	−0.38
$\delta^{EU}_{t\pm j}, y_t$	0.21	−0.19	−0.53	−0.73	−0.74	−0.63	−0.35	0.04	0.21
$\delta^{EN}_{t\pm j}, y_t$	−0.12	−0.01	0.22	0.38	0.43	0.46	0.35	0.08	−0.22
$\delta^{EU+EN}_{t\pm j}, y_t$	0.10	−0.20	−0.34	−0.40	−0.37	−0.25	−0.06	0.09	0.03

Notes: (a) y is real GDP. (b) All variables are logged; then they are either first differenced or are filtered using the Hodrick–Prescott filter (with smoothing parameter 1,600 or 10^5) or with the Baxter–King filter. Panel (b) reports only results with the Hodrick–Prescott filter, using smoothing parameter 1,600. (c) $\sigma \cdot / \sigma_y$ is the relative standard deviation, where the standard deviation of filtered GDP is in the denominator. (d) For the Shimer (2007) data the following computations were used: (i) Define λ_t^{XY} as the Poisson arrival rate of a shock that moves a worker from state $X \in \{U, E, N\}$ to another state during period t. $\Lambda^{XY} = 1 - e^{\lambda_t^{XY}}$ is the associated full-period transition probability. The series λ_t^{NE} and λ_t^{UE} are available from Shimer's website (see http://home.uchicago.edu/~shimer/data/flows/). (e) To obtain P^{UE+NE}, the following formula was used:

$$P^{UE+NE} = \left(1 - e^{\lambda_t^{UE}}\right) * \frac{CPS\_U}{CPS\_U + CPS\_N} + \left(1 - e^{\lambda_t^{NE}}\right) * \frac{CPS\_N}{CPS\_U + CPS\_N},$$

where *CPS_U* is quarterly average of monthly SA CPS data on the number of unemployed; *CPS_N* is quarterly average of monthly SA CPS data on the number of persons "not in the labor force." (f) For Shimer II the *JF* probability was calculated from the job-finding rate f_t, given in the above web page using $F_t = 1 - e^{-f_t}$. In Shimer (2007) F is given by: $F_t = 1 - (u_{t+1} - u^s_{t+1})/u_t$ where $u_{t+1} =$ number of unemployed in period $t+1$, $u_t =$ number of unemployed in period t and $u^s_{t+1} =$ short-term unemployed workers, who are unemployed at date $t+1$ but held a job at some point during period t. An explanation of how short-term unemployment was calculated may be found in Shimer (2007, Appendix A).



(a) Original series p^{UE}

(b) Original series δ^{EU}

(c) HP filtered p^{UE}

(d) HP filtered δ^{EU}

Fig. 1. Job finding and separation rates
Notes: BFF = Bleakley *et al.* (1999) data; S = Shimer (2007) data.

Co-movement. Generally across studies the following hold true:

(i) Hiring rates from unemployment to employment (M^{UE}/E) are countercyclical, while hiring rates from out of the labor force to employment (M^{NE}/E) are pro-cyclical. Summing up the two $(M^{UE} + M^{NE})/E$ yields a flow that is moderately countercyclical.

The first result may seem counterintuitive—flows from unemployment into employment increase in recessions and fall in booms. But note that $M = pU$. The job-finding rate p falls and U rises in recessions, as one would expect intuitively. As the latter effect is stronger than the former effect M rises in recessions. Moreover, E falls at those times. Hence M/E rises in recessions.

(ii) Job-finding rates from unemployment to employment (p^{UE}) are pro-cyclical.

(iii) Separation rates from employment to unemployment (δ^{EU}) are countercyclical, while those from employment to out of the labor force (δ^{EN}) are pro-cyclical. Summing up the two (δ^{EU+EN}) yields a flow that is moderately countercyclical.

(iv) The cross-correlation analysis of the last panel in Table 3 indicates that these cyclical patterns hold true at leads and lags of up to six months.

Volatility. Across studies the following hold true:

(i) Hiring rates M/E, job-finding rates p, and separation rates δ are highly volatile, roughly two to four times the volatility of real GDP.
(ii) Hiring rates from unemployment to employment (M^{UE}/E) are less volatile than the corresponding separation flows (δ^{EU}).
(iii) The reverse is true for flows between out of the labor force and employment, i.e., M^{NE}/E is more volatile than δ^{EN}.
(iv) The sum of the hiring flows $(M^{UE}+M^{NE})/E$ is less volatile than the sum of the separation flows (δ^{EU+EN}).
(v) There is no agreement across studies about the relationship between the volatility of the job-finding rate p^{UE} and the volatility of the separation rate δ^{EU}. In the Blanchard and Diamond (1989, 1990) and Ritter (1993) data the latter is more volatile than the former across all filtering methods; in the Bleakley *et al.* (1999) data this is generally so too, but using the 10^5 HP filter they have almost the same volatility; in Fallick and Fleischmann (2004) separations are more volatile than hirings, but under the low-frequency HP filter this relation is reversed; the Shimer (2007) data indicate that for most filtering methods the opposite holds true, i.e., p^{UE} is more volatile than δ^{EU}. These inconsistencies may be due to a changing relationship between job finding and separation over time, as it was noted that the *UE* and *EU* flows are measured similarly across studies for a given period of time. Note too, that even for the Shimer data the volatility of aggregate job finding p^{UE+NE} is very similar to that of aggregate separations δ^{EU+EN}.

Data Interpretation. It is possible to use any data set to substantiate each of the contradictory interpretations discussed above. Two examples may serve to illustrate. To support the earlier view on the importance of separations, one could even use the Shimer (2007) results. Thus, the volatility of δ^{EU} is higher than M^{UE}/E in his data—see Panel (b) of Table 3—and both have about the same cyclicality under all filtering methods. To support the more recent Hall–Shimer view on the importance of job finding, one could use the Bleakley *et al.* (1999) results. Thus the volatility of p^{UE} is higher than the volatility of δ^{EN} or δ^{EU+EN} and the cyclicality of job finding is stronger under all filtering methods. Why, then, the debates? This is mostly due to the fact that researchers have looked at different objects, as illustrated in these two examples. There is a difference between the behavior of the hiring rate M/E and the job-finding rate p and there is a difference between looking at narrower flows (such as flows between U and E) and wider ones (such as adding flows between N and E or E to E flows). The latter point is manifested in the declining volatility and cyclicality of the separation rate, as more flows out of employment are considered. This is so because the cyclical behavior of the different components of the separation rate move in opposite directions, a point emphasized by Davis (2005). The key compositional issue is that layoffs are countercyclical and quits are pro-cyclical according to many sources of evidence; see, for example, the Bleakley *et al.* (1999) findings cited in Section II above. If, as this evidence suggests, layoffs contribute mostly to the EU flow and quits to the EN and EE flows, then the wider is the separation flow measure, the less volatile and cyclical will it be.

Implications

There are three key implications of these cyclical findings for the study of the evolution of unemployment.

(i) Outflows and Inflows Move Together. Rewriting equation (1) I get:

$$\frac{U_{t+1}}{U_t} - 1 = -p_t^{UE} + \frac{\delta_t^{EU}}{U_t/E_t} + \frac{F_t^{NU} - F_t^{UN}}{U_t}. \tag{4}$$

The equation shows that the dynamics of unemployment depend on the job-finding rate, on the separation rate, on the rate of unemployment and on the net inflow into unemployment from out of the labor force. Examination of the data—using Bleakley *et al.* (1999)—indicates that the important variables in this equation, in terms of the first two moments, are p_t^{UE} and $\delta_t^{EU}/(U_t/E_t)$.[10] Hence the equation is reasonably approximated by a linear relationship between the job-finding rate and the separation rate (divided by the rate of unemployment). Running this relationship using TSLS yields

[10] The relevant statistics are:

	Mean	Std.	Correlation matrix		
			p_t^{UE}	$\frac{\delta_t^{EU}}{U_t/E_t}$	$\frac{F_t^{NU}-F_t^{UN}}{U_t} - \left(\frac{U_{t+1}}{U_t} - 1\right)$
p_t^{UE}	0.25	0.03	1		
$\frac{\delta_t^{EU}}{U_t/E_t}$	0.12	0.01	0.47	1	
$\frac{F_t^{NU}-F_t^{UN}}{U_t} - \left(\frac{U_{t+1}}{U_t} - 1\right)$	0.02	0.03	−0.06	−0.02	1

the following point estimates and standard errors:

$$p_t^{UE} = \underset{(0.02)}{0.12} + \underset{(0.19)}{1.02} \frac{\delta_t^{EU}}{U_t/E_t}. \tag{5}$$

Basically job finding (p_t^{UE}) and separation into unemployment divided by unemployment $[\delta_t^{EU}/(U_t/E_t) = (S_t^{EU}/U_t)]$ move together along a 45-degree line. In a boom (recession) unemployment U_t/E_t and the rate of separation δ_t^{EU} are both low (high). Because unemployment has the stronger effect, the ratio $\delta_t^{EU}/(U_t/E_t)$ is high (low) and so is the job-finding rate p_t. These cyclical relationships are an expression of the pro-cyclicality of p^{UE} and the countercyclicality of δ^{EU} discussed above, in conjunction with the well-known countercyclicality of the unemployment rate U_t/E_t. Going back to equation (4), unemployment growth $[(U_{t+1}/U_t) - 1]$ is fairly stable, as p_t^{UE} and $\delta_t^{EU}/(U_t/E_t)$ move together, rising together in booms and falling together in recessions. In other words, job finding (leading to outflows from unemployment) moves together with inflows to unemployment (due to separations from employment).

(ii) The Ratio of the Separation and Job-finding Rates Approximate the Rate of Unemployment Well. Another way of looking at this issue is to re-write and approximate (4) as follows:

$$\frac{U_t}{E_t} \approx \frac{\delta_t^{EU}}{p_t^{UE}}. \tag{6}$$

This relation would hold exactly true in steady state and with $F_t^{NU} - F_t^{UN} = 0$. Figure 2 shows CPS data on actual U_t/E_t and predicted U_t/E_t, using δ_t^{EU}/p_t^{UE}, based on the Blanchard and Diamond (1989, 1990), Bleakley *et al.* (1999) and Shimer (2007) data sets.

The predicted series have high pairwise correlations with the actual series: 0.91 (Blanchard and Diamond data), 0.91 (Bleakley *et al.* data), and 0.90 (Shimer data). They are also highly correlated between themselves and have very similar moments in their overlapping periods. The latter result mirrors the finding discussed above, whereby the gross flows between E and U are measured similarly across data sets. The high correlation with the actual series is encouraging both for the computation of δ^{EU} and p^{UE} and for the approximation of the unemployment rate. The figure does indicate a difference in mean and variance with actual U_t/E_t, probably due to the fact that it does not depict a steady state and $F_t^{NU} - F_t^{UN}$ is not zero in this sample.

(iii) Both Separation and Job Finding Matter for Unemployment. Figure 3 shows for the three data sets the predicted U_t/E_t series (the same one as in Figure 2) and two alternative, counterfactual predictions: one

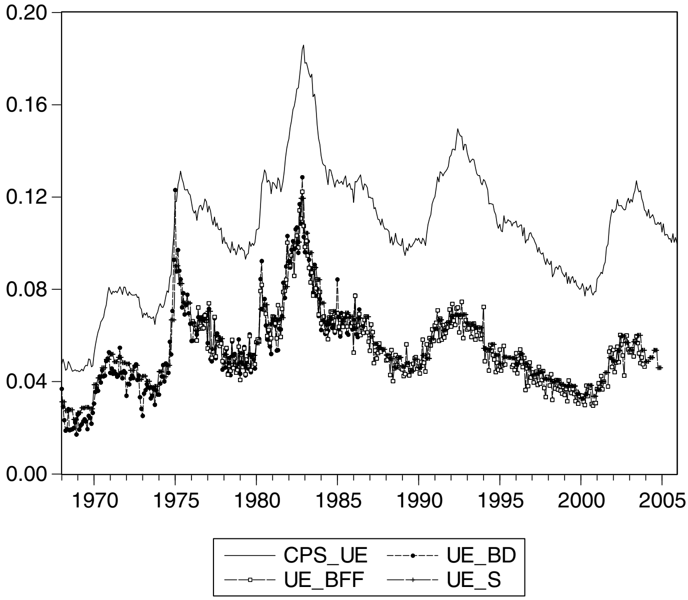


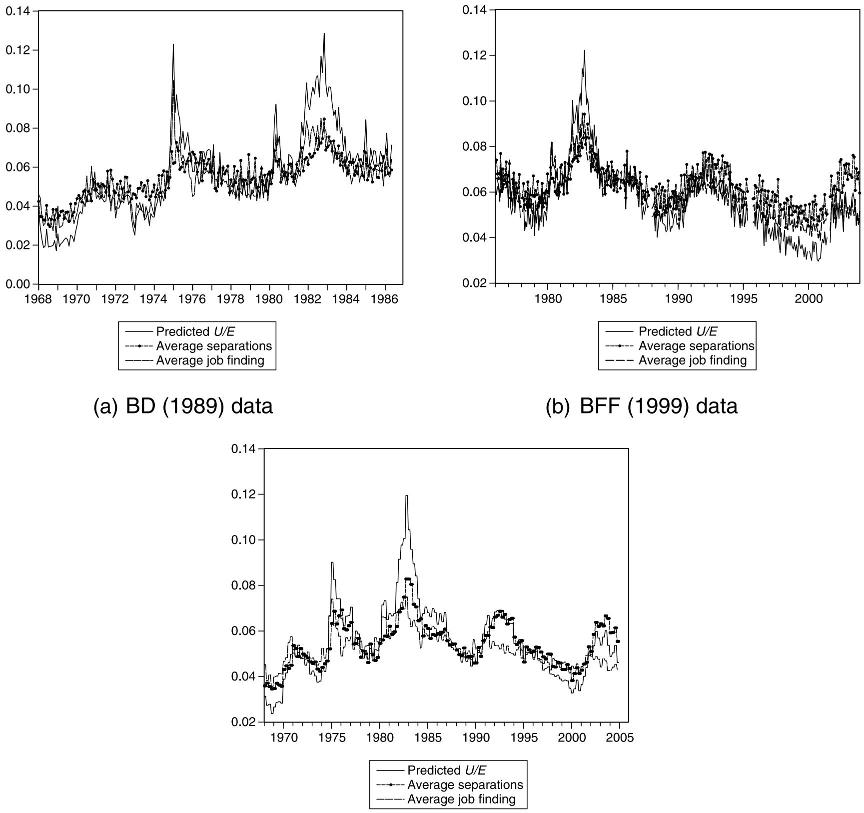
Fig. 2. Unemployment dynamics

using $p_t^{UE}/avg(\delta_t^{EU})$ and one using $avg(p_t^{UE})/\delta_t^{EU}$. Table 4 shows a variance decomposition of U_t/E_t and a correlation analysis using these counterfactuals. The counterfactuals are of interest as they take out either the variability of p^{UE} or of δ^{EU}; if one of these predictors has a high correlation with the actual unemployment rate while the other does not, we can deduce which rate plays a role and which does not.

Figure 3 and Table 4 show no substantial indication that any one of the two alternative counterfactual "predictions" accounts for the unemployment rate more than the other. Visually the series appear similar and the visual impression is confirmed by the variance decomposition and correlation analyses. If anything, relying on the Blanchard and Diamond (1989, 1990) data, and to a lesser extent on the Bleakley *et al.* (1999) data, the role of δ^{EU} is somewhat greater. Overall, the graph and statistics imply that one cannot assign a substantially greater role for p^{UE} or for δ^{EU} in generating unemployment fluctuations.[11]

[11] Shimer (2007) presents a similar exercise in his Figure 5. He notes that in the period 1985–2005 the separation rate (δ^{EU}) plays a diminishing role while job finding (p^{UE}) plays a major one. For the Shimer series shown in Figure 3(c) this is manifested as

$$\rho\left(\frac{U}{E}, \frac{p_t^{UE}}{avg(\delta_t^{EU})}\right) = 0.88, \quad \text{while} \quad \rho\left(\frac{U}{E}, \frac{avg(p_t^{UE})}{\delta_t^{EU}}\right) = 0.77$$



(a) BD (1989) data

(b) BFF (1999) data

(c) Shimer (2007) data

Fig. 3. Counterfactual exercises

V. Additional Features of the Data

The preceding discussion focused on the business-cycle properties of the key series. I turn now to additional issues, not directly related to cyclical topics, that are important for the understanding of labor market dynamics.

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for this subperiod. But for the whole sample the difference between the correlations is very small, as seen in Table 4. For the other two data sets the small differences suggest a slightly greater role for the separation rate; i.e.,

$$\rho\left(\frac{U}{E}, \frac{p_t^{UE}}{avg(\delta_t^{EU})}\right) < \rho\left(\frac{U}{E}, \frac{avg(p_t^{UE})}{\delta_t^{EU}}\right).$$

Table 4. *Approximation of U/E*

(a) Variance decomposition:

$$\ln\frac{p}{\delta} = \ln\frac{p_t^{UE}}{avg(\delta_t^{EU})} + \ln\frac{avg(p_t^{UE})}{\delta_t^{EU}} + \ln\frac{avg(\delta_t^{EU})}{avg(p_t^{UE})}$$

	BD (1989, 1990)	BFF (1999)	S (2007)
$\ln\frac{p}{\delta}$	0.06	0.07	0.06
$\ln\frac{p_t^{UE}}{avg(\delta_t^{EU})}$	0.01	0.02	0.02
$\ln\frac{avg(p_t^{UE})}{\delta_t^{EU}}$	0.03	0.03	0.02
$\mathrm{cov}\left(\ln\frac{p_t^{UE}}{avg(\delta_t^{EU})}, \ln\frac{avg(p_t^{UE})}{\delta_t^{EU}}\right)$	0.01	0.01	0.01

(b) Correlation with p^{UE}/δ^{EU}

	BD (1989, 1990)	BFF (1999)	S (2007)
$\frac{p_t^{UE}}{avg(\delta_t^{EU})}$	0.83	0.86	0.90
$\frac{avg(p_t^{UE})}{\delta_t^{EU}}$	0.93	0.92	0.87

Notes: See notes to Table 1.

The Job-finding Rate

In order to understand the behavior of the job-finding rate, a key issue that needs to be addressed is the size of the relevant pool of searching workers. This issue concerns the pool of workers out of the labor force N. Noting that this rate is $p = M/U$ the preceding discussion raises two issues: first, there are discrepancies in the measurement of the numerator M in all that concerns flows from N to E; second, there is a question as to what is the relevant denominator U in the data. Because of the large N to E flows, the latter is not just the official unemployment pool but a bigger one.

The issue of M^{NE} measurement relates to the discussion in Section III above. Thus, flows series are measured differently across studies, probably due to the different adjustment methods used.

The second issue, namely what is the "correct" pool in the denominator, has received attention in the literature. Jones and Riddell (2000) have studied transition behavior for individuals matched month-to-month using data from the redesigned U.S. CPS in the period 1994–1998. They allow for three non-employment states: unemployed, marginally attached and unattached. The last two groups constitute the "out of the labor force" pool.

They estimate a monthly transition rate into employment for the unemployed group (see their Figure 1), ranging between 20 and 35 percent, which is in line with the results of Table 1(a). Their estimated monthly transition rates into employment for the other two groups, the marginally attached and the unattached, ranges from about 10–20 percent for the former and about 4–5 percent for the latter. The Shimer (2007) data have an average of 4.2 percent for the "out of the labor force" job-finding rate when using the same sample period. Hence comparing the Jones–Riddell and Shimer estimates suggests that the micro and macro estimates are not consistent.[12] A more comprehensive micro–macro comparison study is called for, as well as further study of the flows in the numerator of the job-finding rate.

Flows In and Out of the Pool Out of the Labor Force

The preceding discussion suggests that flows between out of the labor force and employment may be important. It is therefore natural to study the size and behavior of flows into and out of this pool (*N*). The pool (the stock) is sizable: in the period 1948–2005 it averaged almost 58 million people and it currently constitutes about a quarter of the total U.S. population. In the 1950s its size equalled 70 percent of the employment pool; over time this ratio declined to 51 percent.

Using the Shimer (2007) data, the following are the main facts: the monthly gross flows in and out of *N* (to *U* and *E*) have a mean of 2–3 percent of the employment stock, i.e., in the same order of magnitude as the separation flows from employment; their volatility is similar too. The gross flows are 13 to 22 times larger on average as the net flows, with the largest being the *E* to *N* flow, and are three to four times as volatile (in terms of variance) as the net flows. The gross flow between *N* and *U* are countercyclical while flows between *N* and *E* are pro-cyclical. This means that in recessions there is more movement between *N* and *U* in both directions and in booms there is more movements between *N* and *E* in both directions. All the gross flows co-vary positively with each other, and in particular the flows between *N* and *U* (in both directions) and between *N* and *E* (in both directions) are highly correlated. These sets of facts are related: the net flows have much lower magnitude, in terms of the first two moments, because the gross flows offset each other.

[12] Jones and Riddell (2000) also estimate transition rates from employment into unemployment at around 1 percent (see their Appendix, Table 3) and into the "out of the labor force" state at 1–2 percent (see their Figures 2 and 3 and Appendix, Table 3). These estimates are in line with the lower findings of Table 1(b).

Table 5. *Net employment growth* $E_t/(E_{t-1}) - 1$

(a) Moments

	Average	Std.	Correlation	Regression DW	Regression R^2
Actual	0.0014	0.0028			
Blanchard and Diamond (1989)	0.0017	0.0032	0.68	1.60	0.51
Ritter (1993)	−0.0012	0.0028	0.72	1.82	0.55
Bleakley, Ferris and Fuhrer (1999)	0.0011	0.0018	0.71	2.04	0.53
Fallick and Fleischmann (2004)	0.0006	0.0023	0.41	2.11	0.20

(b) Decompositions of $E_t/(E_{t-1}) - 1$

	BD (1989)			BFF (1999)		
	Actual	Predicted	Residual	Actual	Predicted	Residual
Mean	0.001727	0.001707	2.00×10^{-5}	0.001343	0.001121	0.000222
Std.	0.003079	0.002490	0.003241	0.002668	0.001754	0.001828
Correlations						
Actual	1			1		
Predicted	0.69	1		0.73	1	
Residual	0.34	−0.45	1	0.77	0.11	1

(c) Residual tests (*Q*-statistics and their *p*-values)

Lag	1	5	10	20
Blanchard and Diamond (1989)	13.52	33.80	51.28	84.49
	(0.00)	(0.00)	(0.00)	(0.00)
Bleakley, Ferris and Fuhrer (1999)	0.23	9.53	18.79	32.43
	(0.63)	(0.09)	(0.04)	(0.04)

Notes: Actual refers to actual $E_t/(E_{t-1}) - 1$ from the CPS. Predicted refers to $[(M_t^{UE} + M_t^{NE})/(E_t)] - \delta_t^{EU+EN}$ as computed by the cited studies. Residual is the difference between actual and predicted.

How Much Are Net Flows Explained?

A basic question that should be asked is: do the computed gross flows account for net employment changes observed in the data? Looking at this question is one way to gauge the validity of the flows computed in the various studies. This is done by comparing the BLS net employment growth series $(E_t/E_{t-1}) - 1$ to the series implied by the gross flows, using $[(M_t^{UE} + M_t^{NE})/(E_t)] - \delta_t^{EU+EN}$. The comparison is reported in Table 5.[13]

The first panel shows relevant moments, for each series in its own subsample period. It also reports the results of a regression of the actual net flows on the predicted ones. Three series are correlated around 0.7 with actual net employment growth and the regression has an R^2-value of around

[13] As I do not have a complete data set of M flows for Shimer, this cannot be computed for his data set.

0.50. The Fallick and Fleischmann (2004) series has a lower correlation and much lower mean and volatility. From the three series that are better correlated, Ritter (1993) has a negative mean. This leaves two series—Blanchard and Diamond (1989) and Bleakley *et al.* (1999)—that have reasonably close moments (mean and standard deviation) to the actual ones.

The second panel looks at these two studies. This panel relates to the relevant subperiod of the sample, considering the actual and predicted series as well as the residual, which is obtained by subtracting the measured $[(M_t^{UE} + M_t^{NE})/(E_t)] - \delta_t^{EU+EN}$ from the actual $(E_t/E_{t-1}) - 1$. For the Blanchard and Diamond (1989) series the residual is zero on average and the standard deviation of the predicted series is 81 percent of the actual one. But this residual has substantial negative correlation with the predicted part, indicating that it is not just noise. This is also in line with the high Durbin–Watson statistic reported in the first panel and the Ljung–Box Q-statistics in the third panel. For the Bleakley *et al.* (1999) series the residual is somewhat higher than zero on average and the standard deviation of the predicted series is 66 percent of the actual one. But this residual has low correlation with the predicted part, the Durbin–Watson statistic reported in the first panel is around 2, and the Ljung–Box Q-statistics in the third panel indicate that the null hypothesis of no autocorrelation (up to lag k) is usually not rejected.

If one is to judge the gross flows by their ability to account for the net flows, then Table 5 indicates that three out of the four series suffer from various problems. The one series that performs better seems to have prediction errors that are noise, but it explains only 45 percent of the variance of actual net growth. There can be many reasons for these discrepancies. One possible explanation has to do with seasonal adjustment. While all series are seasonally adjusted, the gross flows are seasonally adjusted individually. A linear combination of these adjusted gross flows ($[(M_t^{UE} + M_t^{NE})/(E_t)] - \delta_t^{EU+EN}$, each flow adjusted separately) does not necessarily yield the same series as the adjusted total net flows (the same expression, $[(M_t^{UE} + M_t^{NE})/(E_t)] - \delta_t^{EU+EN}$, seasonally adjusted as one expression).

The bottom line is that the gross flows are unable to fully explain the net flows, casting a shadow over their validity and usefulness.

VI. Conclusions: U.S. Labor Market Facts and Open Issues

The paper began with the statement that the picture of U.S. labor market dynamics is opaque. It turns out that some issues can be clarified while others require further investigation. In order to determine U.S. labor market facts that can be agreed upon so as to guide modeling, I present the facts that are supported across studies and subsequently the open issues left for further study.

U.S. Labor Market Facts

There is basic agreement across data sets and filtering methods that hiring rates and separation rates are countercyclical for flows between unemployment and employment, pro-cyclical for flows between out of the labor force and employment, and countercyclical for aggregate flows (the sum of flows between non-employment and employment). Job-finding rates out of unemployment are pro-cyclical. Cross-correlation analysis indicates robustness of the cyclicality patterns at leads and lags of up to six months.

In terms of volatility, hiring rates are of the same order of magnitude as separation rates. Despite disagreements noted below, the volatilities of the job-finding rate p and the separation rate δ in the aggregate flows ($UE + NE$ and $EU + EN$) are also similar. All these rates—hiring, job finding and separation—are highly volatile, in the order of two to four times the volatility of real GDP.

A key implication is that business cycles are characterized by changes in both hiring and separations. Any empirical business-cycle model needs to feature a mechanism whereby, in recessions, vacancies and hiring decrease, job finding becomes more difficult, workers separate from jobs at a faster rate and unemployment rises.

Areas of Disagreement

As the discussion above has revealed, there are issues not agreed upon that necessitate further investigation. While flows between employment and unemployment are measured similarly across studies, flows between N and E are problematic—the series are not the same across data sets and the data are only partially consistent with micro-based studies. Shimer's (2007) treatment of the data indicates that time aggregation is an issue to be considered, otherwise some transitions are not well captured. The fit of the gross flows with net employment growth data differs across studies and is not high. Finally, there are basically two contradictory findings as to the volatility of p^{UE} vs. δ^{EU} across data sets and filtering methods: some data sets, notably the Blanchard and Diamond (1989) set, show that separation rates are much more volatile than job-finding rates; others, notably the Shimer (2007) data, find that the reverse holds true.

How can one understand these discrepancies and inconsistencies across data series and the debates on the interpretation of the data? The former are due to the different treatment of the data, in particular differences in adjustment methods. Hence only further study of the raw data, paying more attention to consistent adjustment, may lead to the creation of a more credible data set. It could also be true that cyclical patterns have changed over time. The latter issue—the different data interpretations—are due partly to the former (data differences) and partly to the fact that different authors were comparing different objects. Two main differences were noted: (i) the earlier studies were comparing hiring rates M/E to separation rates δ, while the later studies were comparing job finding $p = M/U$ to separations δ. (ii) Some authors have been comparing flows into and out of employment ($UE + NE$ and $EU + EN$) as opposed to others comparing total flows which include job-to-job movements ($UE + NE + EE$ and $EU + EN + EE$).

The resulting picture of labor market dynamics is simultaneously less confusing, given the agreed facts, and in need of further study, given the disagreements and inconsistencies. While the *UE* picture is, to a large extent, established, the *NE* picture is murky. It is important that it be clarified, as flows are substantial and there is no complete characterization of the job-finding and separation rates without it. Wage behavior, for example, depends on these rates and cannot be fully understood without the needed facts. The cyclical behavior of *NE* and *EN* flows is distinct and sometimes contradictory to *UE* and *EU* flows, so more work needs to be done before U.S. labor market dynamics are adequately characterized. Such work would probably need to involve micro studies, as the "out of the labor force" pool is probably comprised of a number of sub-pools with their own specific behavior.

Appendix

Data Sources

The Current Population Survey (CPS) is a household survey and offers a worker perspective. The Job Openings and Labor Turnover Survey (JOLTS) data are based on a survey of employers. The CPS is a sample of 60,000 households with basic labor force data gathered monthly. It relates to the civilian non-institutional population 16 years and older. This survey is the main basis for the data sets analyzed in this paper. JOLTS, too, is conducted by the Bureau of Labor Statistics of the U.S. Department of Labor. The survey collects monthly job openings and labor turnover data from about 16,000 establishments on a voluntary basis. The data include employment, job openings, hires, quits, layoffs and discharges, and other separations. JOLTS defines Employment as all persons on the payroll who worked during or received pay for the pay period that includes the 12th of the month, Job Openings as all positions that are open (not filled) on the last business day of the month, Hires as all additions to the payroll during the month, and Separations as all employees separated from the payroll during the calendar month. The data are available from December 2000 onward. For a discussion of this data set, including some caveats, see Faberman (2005). In particular he notes that respondents tend to be more stable, on average, causing the JOLTS rates to understate true turnover rates.

Filtering the Gross Flows Series

Beyond first differencing, I use two filters: the Hodrick–Prescott (HP) and the Baxter–King (BK) filters. The HP filter is a two-sided linear filter that computes the smoothed series s of y by minimizing the variance of y around s, subject to a penalty that constrains the second difference of s. The BK filter is used to isolate the cyclical component of a time series by specifying a range for its duration. It is a band-pass filter, which is essentially a linear filter that takes a two-sided weighted moving average of the data, where cycles in a "band", given by a specified lower and upper bound, are "passed" through, or extracted, and the remaining cycles are "filtered" out. For a discussion of the merits and drawbacks of these filters, see Burnside (1998), Canova (1998), Baxter and King (1999) and Christiano and Fitzgerald (2003). Table 3 in the main text shows that the filtering method matters. The filtered series are substantially less volatile than the original series, first differencing yields different patterns than the other methods, and the Baxter–King filtered series is less volatile than the HP filtered series. The Baxter–King band-pass filter indicates that there is much high-frequency movement in both p and δ (beyond seasonality). Note, too, that the key comparison—the one between p and δ—depends on the filtering method. It should also be noted that Figure 1 exhibits substantial similarity between the filtered series across the different studies (and even between the original series), albeit not in absolute magnitude.

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